

CRANFIELD UNIVERSITY

NUR IZYAN BT. ZULKAFI

OPERATIONAL AND MAINTENANCE PLANNING OF  
PRODUCTION AND UTILITY SYSTEMS IN PROCESS  
INDUSTRIES

SCHOOL OF WATER, ENERGY AND ENVIRONMENT  
PhD in Energy and Power

PhD

Academic Year: 2018 - 2019

Supervisor: Dr Dawid Hanak  
Associate Supervisor: Prof Gary Leeke  
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## **ABSTRACT**

Major process industries have installed onsite the utility systems that can generate several types of utilities for meeting the utility requirements of the main production systems. A traditional sequential approach is typically used for the planning of production and utility systems. However, this approach provides suboptimal solutions because the interconnected production and utility systems are not optimised simultaneously. In this research, a general optimisation framework for the simultaneous operational and maintenance planning of utility and production systems is presented with the main purpose of reducing the energy needs and resources utilisation of the overall system. A number of industrial-inspired case studies solved show that the solutions of the proposed integrated approach provides better solutions than the solutions obtained by the sequential approach. The results reported a reduction in total costs from 5% to 32%. The reduction in total costs demonstrate that the proposed integrated approach can result in efficient operation of utility systems by avoiding unnecessary purchases of utility resources and improved utilisation of energy and material resources. In addition, the proposed integrated optimisation-based model was further improved with the presence of process uncertainty in order to address dynamic production environment in process industries. However, integrated planning problems of production and utility systems results to large mixed integer programming (MIP) model that is difficult to solve to optimality and computationally expensive. With this regards, three-stage MIP-based decomposition strategy is proposed. The computational experiments showed that the solutions of the proposed MIP-based decomposition strategy can achieve optimal or near-optimal solutions at further reduced computational time by an average magnitude of 4. Overall, the proposed optimisation framework could be used to integrate production and utility systems for effective planning management in the realistic industrial scenarios.

Keywords:

Cleaning, scheduling, production, optimisation, energy supply chain



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## LIST OF ABBREVIATIONS

AIMMS	AIMMS optimisation modelling
APICS	The American Production and Inventory Control Society
CH	Control planning horizon
CHP	Combined heat and power
CPLEX	IBM ILOG CPLEX optimisation studio
GAMS	General algebraic modelling system
GUI	Graphical user interface
LP	Linear programming
MIP	Mixed integer programming
MILP	Mixed integer linear programming
NP	Nonlinear programming
PH	Prediction planning horizon
TH	Total planning horizon

# LIST OF NOMENCLATURES

## Indices / Sets

$e \in E$	resources (products, utilities, emissions)
$i \in I$	units (production, utility, inventory tank, customers)
$j \in J$	tasks (production, conversion, transfer)
$m \in M$	technologies (conversion, transfer, storage)
$n \in N$	scenarios
$q \in Q$	offline cleaning task options
$p \in P$	piecewise segment
$s \in S$	states (material resources, energy forms, undesired substances)
$t \in T$	time periods
$z \in Z$	internal and external zones

## Superscripts

es	earliest
fix	fixed
ls	latest
loss	losses
max	maximum
min	minimum
off	offline
on	onlin
var	variable
+	inlet
-	outlet

## Subsets

$CB_i$	units $i$ that are subject to condition-based cleaning tasks
$CS_i$	customers

$DM_i$	units $i$ that are under in-progress offline cleaning at the beginning of the planning horizon (information carried over from previous planning horizon)
$E^{FUEL}$	fuel resources
$E^{EMIS}$	emissions
$E^{NS}$	product resources for which batch splitting is not allowed
$E^{NM}$	product resources for which batch mixing is not allowed
$E_i$	resources that can be produced in unit $i$
$E^{PR}$	product resources
$E^{UT}$	utility resources
$FM_i$	units $i$ that are subject to flexible time-window offline cleaning
$IC_i$	units or inventory tanks that can be connected to or from unit or inventory tank or customer $i$
$I_e$	units that can consume or produce resource $e$
$I^{BL}$	boilers
$I^{TB}$	turbines
$I^{SF}$	units that are subject to startup and shutdown costs
$I^{S-\min}$	units that are subject to minimum runtimes
$I^{F-\min}$	units that are subject to minimum shutdown times
$I_e^{PR}$	production units that require utility resource $e$ to operate
$IT_e$	inventory tank that can store resource $e$
$J_e$	task that could consume or produce product resource $e$
$J_i$	task that can be performed by production unit $i$
$J_s$	tasks that consume or produce state $s$ (input or output state)
$J_s^{TT}$	tasks that could transfer state $s$
$J_s^{RM}$	tasks that involve raw material state $s$
$M^{CT}$	conversion technologies
$M^{TT}$	transfer technologies

$M^{ET}$	local exploitation technologies
$M^{ST}$	storage technologies
$M_j$	technologies that could perform task $j$
$M_s$	technologies that involve state $s$
$M_z$	technologies that could be installed in zone $z$
$M_z^{ET}$	local exploitation technologies in zone $z$
$M_z^{CE}$	conversion and local exploitation technologies in zone $z$
$M_{(z,z')}^{TT}$	transfer technologies that can transfer states from zone $z$ to $z'$
$M_{(s,z)}^{ST}$	storage technologies for state $s$ in zone $z$
$MR_i$	units $i$ that are subject to maximum runtime constraints
$PR_i$	production units
$Q_i$	alternative offline cleaning task options for unit $i$
$S_z$	states that are present in zone $z$
$S_z^{RM}$	raw materials states in zone $z$ (principal states)
$S^{NR}$	non-renewable raw materials states
$S_z^{FP}$	states $s$ that have demand in zone $z$ (demand states)
$S_z^B$	storable states $s$ of zone $z$
$S_z^D$	disposal states $s$ of zone $z$
$UT_i$	utility units
$Z^in$	internal zones of the energy supply chain network
$Z_z^{TT}$	zones that are connected to zone $z$ (transfer of states to zone $z$ )
$ZI_i$	inventory tanks

## Parameters

$\alpha_{(i,e,e')}$	coefficient for production unit $i$ that provides the variable needs for utility $e$ for the production of a unit of product $e'$
---------------------	-----------------------------------------------------------------------------------------------------------------------------------

$\alpha_{(j,i,e)}$	coefficient for task $j$ of production unit $i$ that provides the variable needs for utility resource $e$
$\alpha_{(z,z,j,m,t)}$	bounds on the available capacity for conversion and transfer task
$\bar{\alpha}_{(i,e,e')}$	coefficient for production unit $i$ that provides the fixed needs for utility resources $e$ for the production of resources $e'$
$\bar{\alpha}_{(j,i,e)}$	coefficient for task $j$ of production unit $i$ that provides the fixed needs for utility resource $e$
$\alpha_{(e',e)}^{EMIS}$	coefficient of emission $e'$ released from the use of fuel resource $e$
$\alpha_i^{MP}$	coefficient of MP steam redirected to boiler $i$
$\alpha_i^{EL}$	coefficient of electricity required for operation of boiler $i$
$\alpha_i^{EHST}$	coefficient of exhaust steam during the operation of turbine $i$
$\beta_i$	bounds on the capacity of unit $i$
$\beta_i^{loss}$	coefficient of losses in inventory tank $i$
$\beta_{(z,s,t)}^{\min}$	bounds on the inventory level for states that can be stored $s \in S^B$
$cv_e$	calorific value of fuel resource $e$
$\delta_i$	performance degradation rate for unit $i$ due to its cumulative time of operation
$\delta_i^{cd}$	performance coefficient related to operating level for unit $i$ due to its cumulative deviation from its reference operating level
$\delta_n^p$	probability of occurrence for each scenario $n$
$\varepsilon_{(e,i)}$	bounds on inventory level of fuel resource $e$ in inventory tank $i$
$\varepsilon_{(e,i,t)}$	bounds on the total inlet/outlet flow of resource $e$ to/from inventory tank $i$ in time period $t$
$\varepsilon_{(z,m,t)}^{CES0}$	investment cost required to establish a technology
$\varepsilon_{(z,m,t)}^{CES}$	investment cost required to increase the capacity of a technology

$\varepsilon_{(z,z',m,t)}^{TT0}$	investment cost required to establish transfer technology
$\varepsilon_{(z,z',m,t)}^{TT}$	investment cost required to increase the capacity of transfer technology
$\xi_{(e,i)}$	bounds on the capacity of inventory tanks $i$ that can store resources $e$
$\xi_{(e,i,i')}$	maximum amount of product resource $e$ that can flow between unit $i$ and $i'$
$\zeta_{(e,t)}$	demand for product resource $e \in E^{PR}$ in time period $t$
$\zeta_{(z,s,t)}$	demand for final product states $s \in S^{FP}$ in zone $z$ in time period $t$
$\gamma_i^{on}$	minimum time between two consecutive online cleanings in unit $i$
$\gamma_{(z,m,t)}$	bounds on the capacity expansion for conversion and storage technologies
$\gamma_{(z,z',t)}^{TT}$	bounds on the capacity expansion for transfer technology $j \in J^T$
$fuel_{(e,i)}^s$	amount of fuel that is used during starts up of the boiler $i$
$ft_{(e,i,p)}$	amount of fuel resource $e$ that can be consumed by the boiler $i$ for each piecewise segment $p$
$ft_{(e,i)}$	amount of fuel resource $e$ that can be consumed by the boiler $i$
$h_b$	enthalpy values of superheated steam
$h_{fw}$	enthalpy values of feed-water heaters
$h_m$	enthalpy values of medium pressure steam
$h_l$	enthalpy values of low pressure steam
$h_e$	enthalpy values of exhaust steam
$K_{(i,t)}$	bounds on the operating level for utility unit $i \in UT_i$ in time period $t$



$\bar{K}_{(e,i,t)}$	bounds on the production level of product resource $e \in E^{PR}$ for production unit $i \in PR_t$ in time period $t$
$K_{(s,j,m)}$	coefficient for input/output states for tasks $j$ that can perform technology $m$
$\lambda_{(e,i)}^B$	percentage coefficient that determines the minimum level for each resource inventory tank at the end of the prediction horizon (terminal value)
$\lambda_i^U$	percentage coefficient that determines the maximum extra energy consumption level for operating unit $i$ at the end of the prediction horizon (terminal value)
$\lambda_{(z,s,t)}^{ST}$	inventory cost for the states that can be stored
$\lambda_{(z,s,t)}^D$	penalty cost for the release of the materials/energy/undesired substances states to the environment
$\lambda_{(z,s,t)}^L$	lost sale for unsatisfied demand
$\rho_{(e,j)}$	conversion coefficient of product resource $e$ in task $j$
$\rho_{(e,i)}^{COGEN}$	stoichiometry coefficient that relates the operating level of the utility unit $i$ with the generated amount of each cogenerated utility resource $e$
$\rho_{(e,i,p)}^{FUEL}$	gradient coefficient of boiler $i$ for consuming fuel $e$ for each piecewise segment $p$
$\rho_i^{rec}$	performance recovery factor of unit $i$ due to online cleaning
$\mu_{(i,t)}, \bar{\mu}_{(i,t)}$	sufficiently large numbers
$\mu_{(z,m,t)}^{CE}$	necessary installation time for conversion and local exploitation technology $m$ in zone $z$ , if its construction starts in time period $t$
$\mu_{(z,m,t)}^{ST}$	necessary installation time for storage technology $m$ in zone $z$ , if its construction starts in time period $t$

$\mu_{(z,z',m,t)}^{TT}$	necessary installation time for transfer technology $m$ that connects zone $z$ and $z'$ , if its construction starts in time period $t$
$\eta_t^{\max}$	limited amount of available resources for cleaning operations in time period $t$
$\eta_{(e,i,p)}^{FUEL}$	efficiency of fuel resource $e$ in boiler $i$ for each piecewise segment $p$
$\eta_i^{TB}$	efficiency of turbine $i$
$\eta_{(z,s,t)}^{loss}$	losses coefficient for states that can be stored $s \in S^B$
$O_i$	maximum runtime for unit $i$
$\phi$	associated cost coefficients for objective function terms related to utility and production unit $i$ (i.e., variable and fixed operating cost, utilities and products purchase prices, startup and shutdown costs, electricity price, extra energy consumption cost, online and offline cleaning tasks costs)
$\pi_i^{on}$	percentage modification on the upper operating level of unit $i$ that is under online cleaning
$\pi_{(z,s,j,m,t)}$	cost for producing states by performing conversion tasks through conversion technology
$q_{(i,t)}^{ref}$	reference operating level for utility unit $i$ per time period
$q_{(e,i,t)}^{ref}$	reference production level for production unit $i$ that produces product resource $e$ per time period
$qb_i^{ref}$	reference operating level for boiler per time period $t$
$qp_{(e,i,p)}$	amount of HP steam that can be generated by consuming fuel $e$ in the boiler $i$ for each piecewise segment $p$
$\vartheta_{(i,q)}^{off}$	resource requirements for offline cleaning task option $q$ of unit $i$
$\vartheta_i^{on}$	resource requirements for online cleaning of unit $i$

$\vartheta_{(z',z,s,j,m,t)}^{TT}$	cost for transferring the states that are considered as final products $s \in S^{FP}$
$\tau_i$	time information of cleaning task for unit $i$
$\tau_{(i,j)}$	processing time of production unit $i$ that perform task $j$
$\tau_i^{es}$	earliest time of cleaning task for unit $i$
$\tau_i^{ls}$	latest time of cleaning task for unit $i$
$\vartheta_i^{max}$	extra energy consumption limit for unit $i$
$\psi_i$	minimum shutdown idle time for unit $i$
$\nu_{(i,q)}$	duration of offline cleaning task option $q$ that could take place in unit $i$
$\vartheta_i^{max}$	extra energy consumption limit for unit $i$ (performance degradation)
$\psi_i$	minimum shutdown idle time for unit $i$
$\psi_{(z,s,j,m,t)}^{RM}$	raw materials cost
$\omega_i$	minimum runtime for unit $i$
$\omega_{(z,s,t)}$	maximum available amount of raw material states
$\omega_{(z,s)}^{NR}$	maximum available amount of non-renewable states

Parameters (initial state of the overall system)

$\tilde{\beta}_{(e,i)}$	initial inventory level of resource $e$ in inventory tank $i$
$\beta_{(z,s)}^0$	initial inventory level for states
$\tilde{\gamma}_i^{on}$	initial state of utility unit $i \in CB_i^{on}$ with respect to its last online cleaning
$\tilde{\rho}_i$	initial cumulative time of operation for unit $i$
$\tilde{\rho}_i^{cd}$	initial cumulative deviation from the reference operating level for unit $i$

$\tilde{\eta}_{(i,t)}$	time periods $t$ for utility unit $i \in DM_i$ that there is a known cleaning resource requirement (in-progress offline cleaning task from previous planning horizon)
$\tilde{\psi}_i$	total number of time periods at the beginning of the current planning horizon that unit $i$ has been continuously not operating since its last shutdown
$\tilde{\omega}_i$	total number of time periods at the beginning of the current planning horizon that unit $i$ has been continuously operating since its last startup
$\tilde{\chi}_i$	operating status of unit $i$ just before the beginning of the current planning horizon
$\tilde{\chi}_{(e,i)}$	operating status of unit $i$ that consume or produce resource $e$ just before the beginning of the current planning horizon
$\varphi_{(z,m)}$	initial installed capacity for conversion technology $m \in M^{CT}$ and local exploitation technology $m \in M^{ET}$ in zone $z$
$\varphi_{(z,s,m)}^{ST}$	initial installed capacity for storage technology $m \in M^{ST}$ in zone $z$
$\varphi_{(z,z',m)}^{TT}$	initial installed capacity for transfer technology $m \in M^{TT}$ that connects two zones

#### Continuous variables (non-negative)

$B_{(e,i,t)}$	inventory level for resource $e$ in inventory tank $i$ at time period $t$
$B_{(n,e,i,t)}$	inventory level for resource $e$ in inventory tank $i$ at time $t$ for scenario $n$
$B_{(z,s,t)}$	inventory of state $s$ in zone $z$ at the end of time period $t$
$B_{(e,i,t)}^-$	total outlet flow of resource $e$ from inventory tank $i$ at time period $t$

$B_{(n,e,i,t)}^-$	total outlet flow of resource $e$ from inventory tank $i$ at time period $t$ for scenario $n$
$B_{(e,i,t)}^+$	total inlet flow of resource $e$ to inventory tank $i$ at time period $t$
$B_{(n,e,i,t)}^+$	total inlet flow of resource $e$ to inventory tank $i$ at time period $t$ for scenario $n$
$B_{(e,i',i,t)}^{UT,-}$	flow of utility $e$ from inventory tank $i'$ to production unit $i$ at time period
$B_{(n,e,i',i,t)}^{UT,-}$	flow of utility $e$ from inventory tank $i'$ to production unit $i$ at time period $t$ for scenario $n$
$BT_{(i,j,t)}$	batch size of production unit $i$ that perform production task $j$ at time period $t$
$BEL_{(i,t)}$	electricity that is needed by the boiling feed water pump to supply water to the boiler $i$
$D_{(i,t)}$	cumulative operating level deviation for unit $i$ in time period $t$
$D_{(n,i,t)}$	cumulative operating level deviation for unit $i$ in time period $t$ for scenario $n$
$DB_{(z,s,t)}$	quantity of states that can be disposed
$DC_t$	penalty cost for the states that is disposed to the environment(e.g., emissions cost)
$DEM_{(e,t)}^{UT}$	demand for utility resource $e$ at time period $t$
$EC_{(z,m,t)}$	increase of capacity for conversion technology $m$ in zone $z$ in time period $t$
$EC_{(z,z',m,t)}^{TT}$	increase of capacity for transfer technology $m$ that can transfer from zone $z$ to zone $z'$ in time period $t$
$EC_{(z,s,m,t)}^{ST}$	increase of capacity for storage technology $j$ that can store state $s$ in zone $z$ in time period $t$

$EP_{(i,t)}$	exhaust steam from turbine $i$ at time period $t$
$EL_{(i,t)}$	generation of electricity from turbine $i$ at time period $t$
$FC_{(z,m,t)}$	total capacity of conversion technology $m$ in zone $z$ in time period $t$
$FC_{(z,s,m,t)}^{ST}$	total capacity of storage technology $m$ that can store state $s$ in zone $z$ in time period $t$
$FC_{(z,z',m,t)}^{TT}$	total capacity of transfer technology $m$ that can transfer from zone $z$ to zone $z'$ in time period $t$
$FT_{(e,i,i',t)}$	flow of resource $e$ between unit/inventory tank $i$ and unit/inventory tank/customer $i'$ at time period $t$
$FS_{(e,i,t)}$	amount of fuel consumed during starts-up of boiler $i$ that consume fuel resource $e$ at time period $t$
$FA_t$	investment on fixed assets in time period $t$
$FA_t^{TT}$	investment cost for transfer network in time period $t$
$FOC_t$	fixed operating cost in time period $t$
$HP_{(i,t)}$	amount of HP steam that is produced by turbine $i$ at time period $t$
$HPM_t$	amount of HP steam from that is transferred to MP steam mixer at time period $t$
$IC_t$	inventory cost for material states in time period $t$
$LP_{(i,t)}$	amount of LP steam that are extracted from turbine $i$ at time period $t$
$LS_t$	penalty cost for lost sales for states whose demand is not met
$MP_{(i,t)}$	amount of MP steam that are extracted from turbine $i$ at time period $t$
$MPM_t$	amount of MP steam from that is transferred to LP steam mixer at time period $t$

$NS_{(e,t)}^{UT}$	purchases of utility resource $e$ at time period $t$
$NS_{(e,i,t)}^{UT}$	purchases of utility resource $e$ to be utilised in production unit $i \in I_e^{PR}$ in time period $t$
$NS_{(n,e,i,t)}^{UT}$	purchases of utility resource $e$ to be utilised in production unit $i \in I_e^{PR}$ in time period $t$ for scenario $n$
$NS_{(e,t)}^{FP}$	purchases of product resource $e$ in time period $t$ (or lost sales)
$NS_{(n,e,t)}^{FP}$	purchases of product resource $e$ in time period $t$ (or lost sales) for scenario $n$
$PC_t$	production cost for final product states in time period $t$
$PT_{(z,z',j,m,t)}$	quantity of states converted or transferred through task $i$ using technology $j$ from zone $z$ to zone $z'$ in time period $t$
$QE_{(e,i,t)}$	production level of resource $e$ from unit $i$ in time period $t$
$QE_{(n,e,i,t)}$	production level of resource $e$ from unit $i$ in time period $t$ for scenario $n$
$QS_{(i,t)}$	operating level of utility unit $i$ in time period $t$
$QS_{(n,i,t)}$	operating level of utility unit $i$ in time period $t$ for scenario $n$
$\bar{Q}_{(i,t)}^{dev}$	operating level deviation of the utility unit $i$ from its reference operating level in time period $t$
$\bar{Q}_{(n,i,t)}^{dev}$	operating level deviation of the utility unit $i$ from its reference operating level in time period $t$ for scenario $n$
$Q_{(n,e,i,t)}^{dev}$	operating level deviation of the production unit $i$ from its reference operating level in time period $t$ for scenario $n$
$R_{(i,t)}$	cumulative time of operation for unit $i$ in time period $t$
$RC_t$	raw material states cost
$RET_{(i,t)}$	amount of medium pressure steam that entered back to the boiler $i$ to pre-heat water

$U_{(i,t)}$	extra energy consumption (from fully clean condition) of unit $i$ due to its performance degradation
$U_{(n,i,t)}$	extra energy consumption (from fully clean condition) of unit $i$ due to its performance degradation for scenario $n$
$TC_t$	transfer cost for final product states within internal zones and external sales of final product states to external zones
$VOC_t$	variable operating cost in time period $t$ (includes production & inventory & transportation & state purchases)

#### Binary variables

$A_{(e,i,p,t)}$	= 1, if a boiler $i$ that consume fuel resource $e$ for piecewise segment $p$ at time period $t$
$F_{(i,t)}$	= 1, if a unit $i$ shuts down at the beginning of time period $t$
$FE_{(e,i,t)}$	= 1, if a unit $i \in I_e^{SF}$ that consume/produce resource $e$ shuts down at the beginning of time period $t$
$G_{(e,i,t)}$	= 1, if production resource $e$ is delivered to customer $i$ at time period $t$
$H_{(i,q,t)}$	= 1, if the offline cleaning task option $q \in Q_i$ for unit $i \in (CB_i^{off} \cup FM_i)$ starts at the beginning of time period $t$
$S_{(i,t)}$	= 1, if a unit $i$ starts up at the beginning of time period $t$
$SE_{(e,i,t)}$	= 1, if a unit $i \in I_e^{SF}$ that consume/produce resource $e$ starts up at the beginning of time period $t$
$V_{(i,t)}$	= 1, if an online cleaning task for unit $i \in CB_i^{on}$ occurs in time period $t$
$V_{(e,i,t)}^{PR}$	= 1, if an online cleaning task for production unit $i \in (PR_i \cap CB_i^{on})$ that produces product $e \in E^{PR}$ takes place in time period $t$



$W_{(i,t)}$	= 1, if an offline cleaning task for unit $i \in (CB_i^{off} \cup FM_i)$ starts at the beginning of time period $t$
$WC_{(z,m,t)}$	= 1, if conversion or local exploitation technology $m$ is established in zone $z$ in time period $t$
$WS_{(z,s,m,t)}$	= 1, if storage technology $m$ for state $s$ is established in zone $z$ in time period $t$
$WT_{(e,i,i',t)}$	= 1, if a connection exists between unit/inventory tank $i$ and unit/inventory tank/customer $i'$ at time period $t$ to allow the flow of product resource $e$ at time period $t$
$X_{(i,t)}$	= 1, if a unit $i$ is operating during time period $t$
$XS_{(i,t)}$	= 1, if inventory tank $i$ is operating at time period $t$
$XE_{(e,i,t)}$	= 1, if a unit $i \in I_e^{SF}$ that consume/produce resource $e$ is operating during time period $t$
$XP_{(i,j,t)}$	= 1, if production unit $i$ starts production task $j$ at time period $t$
$XZ_{(e,i,t)}$	= 1, if inventory tank $i$ stores product resource $e$ at time period $t$
$Y_{(e,i,t)}$	= 1, if production unit $i \in PR_i$ produces product $e$ in time period $t$
$YC_{(z,m,t)}$	= 1, if capacity of conversion or local exploitation technology $m$ begin installing in zone $z$ in time period $t$
$YS_{(z,s,m,t)}$	= 1, if capacity of storage technology $m$ for state $s$ begin installing in zone $z$ in time period $t$
$YT_{(z,z',m,t)}$	= 1, if capacity of transfer technology $m$ starts installing in zone $z$ in time period $t$



# 1 INTRODUCTION

## 1.1 Research Background

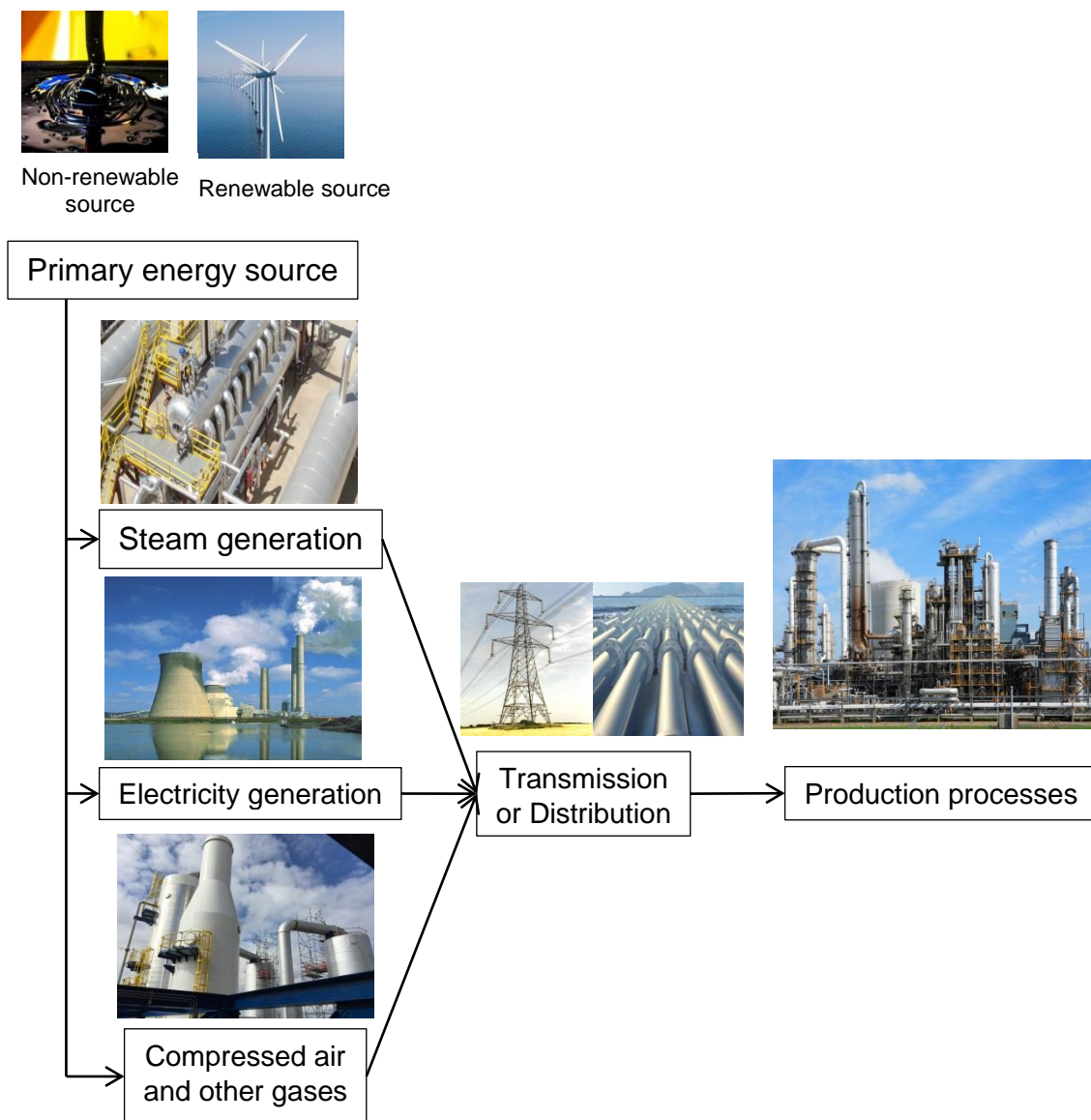
### 1.1.1 Process Industries

According to Fransoo, (1992), The American Production and Inventory Control Society (APICS) described process industries by the following definition: “*Process industries are businesses that add value to materials by mixing, separating, forming or chemical reactions*”. The APICS also proposed a classification of process industries into two major kinds of process industries namely known as batch and continuous process industries. The batch process industries are characterised by multi-stage production with multiple steps and complex routings to produce final products in batches. Continuous process industries are defined as a single-stage production with fixed flow production lines to produce final products continuously without interruption. Examples of continuous process industries are metals, pulp and paper, cement, and petrochemical industries, whereas fine chemicals, pharmaceutical and food industries is typically a batch process industries.

In general, continuous or batch process industries require energy (i.e., electricity and steam) and other types of utilities such as water, compressed air and other gases for the operations of their major process equipment. Figure 1-1 shows the structure of production and utility systems in energy-intensive process industries. Primary source of energy either from non-renewable or renewable energy sources are required for the generation of utilities. Water, steam and other gases are being transferred to the main production systems via pipe distribution network. Meanwhile, electricity is being transmitted from the electricity generation to the production systems via transmission tower.

Most energy-intensive process industries have installed onsite the utility systems to generate utilities for their own consumption in order to produce desired final products. For example, in a refinery operation, major production systems consist of crude distillation units, vacuum distillation units, hydrocracker units, and

delayed coker units. These production systems usually require utilities such as steam, electricity, cooling water, compressed air and other gases in order to produce petroleum products such as gasoline, diesel, and kerosene. These utilities are generated from the refinery's onsite utility systems. The utility systems in a typical refinery may include cogeneration system to supply electricity and steam, air separation system to supply compressed air and also water networks to supply cooling water to the main production systems.

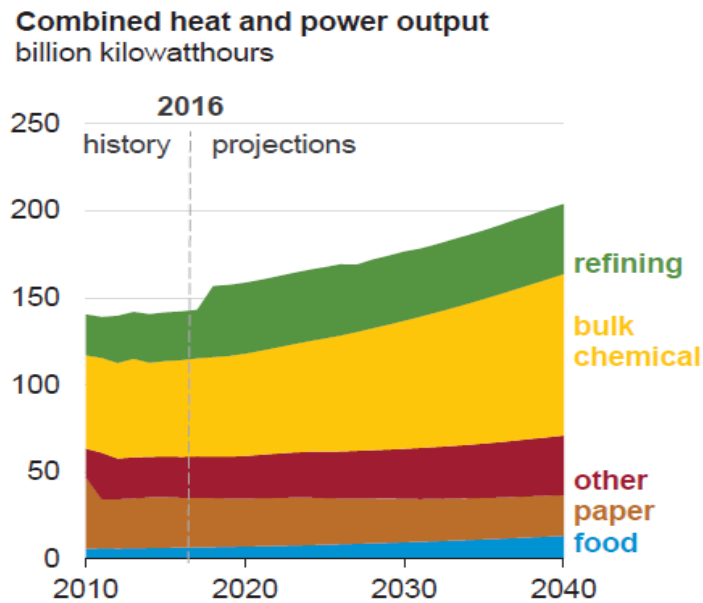


**Figure 1-1 Structure of production and utility systems in energy-intensive process industries**

Process industry is known as the main economic sector globally especially in developing countries. The proportion of world energy consumption is projected to rise 28% between 2015 and 2040, at an average annual growth rate of 1.1%. The world energy use in industrial sector will rise by 0.7% per year during the same period (EIA, 2017). The large part of energy consumption in the process industry depends on the primary source of energy such as fossil fuel, coal and natural gas for the generation of utilities.

The dependency on the primary source of energy for the generation of utilities in energy-intensive process industries may contribute to the effect of global warming due to the emission of greenhouse gases. Intergovernmental Panel for Climate Change (IPCC) suggested a short-term solution to reduce the impact of global warming by improving energy efficiency of the process industries (IPCC, 2014). There are two possible solutions to improve energy efficiency in process industries: (i) advancement in energy production technology (Gvozdenac et al., 2017; Neugebauer et al., 2011) (e.g., combined heat and power system) and, (ii) strategic management of process industries (Bade and Bandyopadhyay, 2015) (e.g., process integration).

One of an important onsite energy production technology (i.e., utility system) in energy-intensive process industry for the steam and electricity generation is known as combined heat and power (CHP). Figure 1-2 shows the output of the CHP in process industries are projected to rise up to 200 billion kilowatt-hours in 2040 (EIA, 2017). The CHP continues to serve as the major utility system to generate electricity and heat in energy-intensive process industries in the near future as it improves overall energy efficiency and reducing greenhouse gas emissions. According to a review by Ackermann, Ran Andersson, and Sö Der (2001), CHP technologies such as combined cycle gas turbines show lower emissions of carbon dioxide and sulphur dioxide than that from coal power stations. These findings on the benefit of CHP technologies was supported by Lund & Mathiesen (2015) as they described that the combined cycle gas turbine was the most feasible technology for large scales CHP.



**Figure 1-2 Combined heat and power output (EIA, 2017)**

There are considerable progress that has been made on strategic management of process industries in the mid-1980s and increasing number of research articles started to be published since 1990s on various topics related to design, supply chain, process integration, operation and maintenance, planning, scheduling and control in process industries. Table 1-1 shows the list of review articles on important issues in process industries.

One of the important issues as shown in Table 1-1 is the application of process integration approach for strategic management in process industries. Early research on process integration through thermodynamics techniques that were known as pinch and energy analysis was published by Hu and Ahmad (1994) and Smith (2000). Since then, process integration has evolved over the years through advancement in optimisation methods for efficient use of resources utilisation, emissions reduction, process operation and energy efficiency (Klemeš, Varbanov, & Kravanja, 2013). The process integration approach is now broadly applied in the field of planning and scheduling at supply chain level (Barbosa-Povoa, 2014) and production level (Baldea & Harjunkoski, 2014).

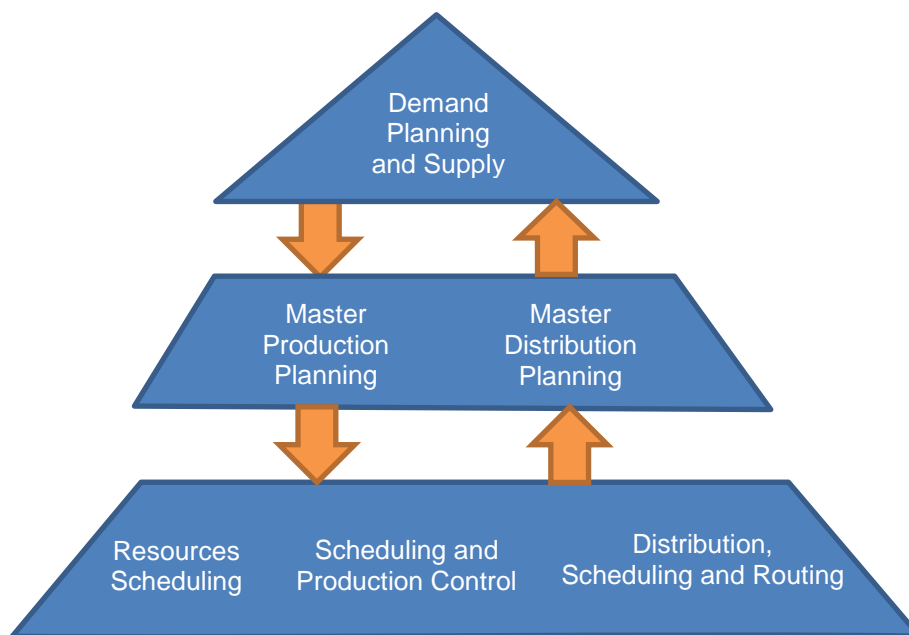
**Table 1-1 Reviews addressing important process industries issues**

Review articles	Main focus in process industries
Gelders (1981)	Production planning
Fransoo (1992)	Demand management and production control
Pistikopoulos (1995)	Uncertainties in design and operation
Shobrys and White (2000)	Planning, scheduling and control
Vassiliadis and Pistikopoulos (2001)	Uncertainties in maintenance and process scheduling
Kallrath (2002)	Planning and scheduling
Grossmann (2005)	Enterprise-wide optimisation
Budai, Dekker and Nicolai (2008)	Maintenance and production
Klemeš, Varbanov and Kravanja (2013)	Process Integration
Baldea and Harjunoski (2014)	Production scheduling and control
Barbosa-Povoa (2014)	Process supply chain
Dias and Ierapetritou (2016)	Scheduling and control under uncertainties
Zhang and Grossmann (2016)	Industrial demand side management
Dias and Ierapetritou (2017)	Integrated decision making strategies

In addition, the concept of enterprise-wide optimisation is used to improve the efficiency of process industry and to find optimal decision making. The decision making in the process industry ranges across different levels, from process control, scheduling, planning to supply chain management. These decision levels

vary in terms of time horizon, optimisation framework, process uncertainties and objectives. Integrated decision-making framework for all decisions levels is proposed through enterprise-wide optimisation, considering advanced modelling techniques and process complexity to solve large-scale problems. Dias and Ierapetritou (2017) stated that one of the challenges for integrated decision-making process by considering all decisions levels is data integration across the different levels. Unified data integration across these levels is essential for effective integrated decision-making approaches.

In addition, strategic supply chain management (i.e., upper level of decision-making) is required to improve efficiency and responsiveness while satisfying customer's demand at minimum operational costs. In order to understand the concept of supply chains management, the relations between the upper and lower levels of supply chains activities should be considered.



**Figure 1-3 Supply chain planning (Barbosa-Póvoa, 2014)**

Figure 1-3 shows the relations of supply chain planning and scheduling in process industries. The supply chain planning can be started at the upper level to match the supply and the demand. The aggregated planning for supply and demand is performed, which then are decomposed into more detailed master planning at the



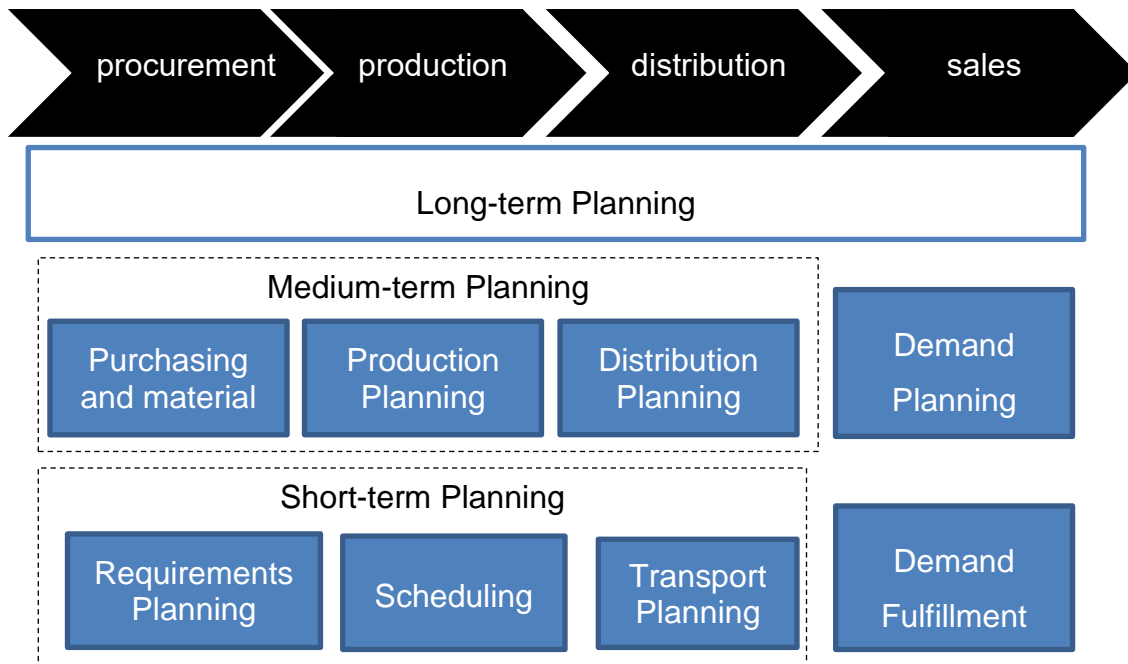
lower levels. The master production and distribution plans are defined within periods of 1 to 3 months. Such master plans are further decomposed into operational planning on weekly or even daily to monitor supply chain activities such as resources, production and distribution scheduling from day to day basis (Barbosa-Póvoa, 2014).

Overall, an integrated enterprise-wide approach that considers the optimisation of all production facilities (e.g., production and utility systems) at all decision-making levels can be very beneficial to totally maximise energy utilisation and minimise environmental impacts in energy-intensive process industries.

### **1.1.2 Planning in Process Industries**

Modern process industries that consist of integrated production and utility systems require an effective planning management in order to fully satisfy the customer's demand by maintaining high production levels at low total costs. In order to achieve this goal, the planning problems in process industries cover a wide range of planning activities such as productions of products, utilities requirements, inventories profiles, maintenance policies, resources utilisation and distributions of products to customers. The traditional management of planning decisions can be divided into three levels of planning: (i) strategic planning (long-term planning horizon); (ii) tactical planning (medium-term planning horizon); and (iii) operational planning (short-term planning horizon).

Figure 1-4 shows the long-term, medium-term and short-term planning matrix. The long-term planning determines the structure of the production facilities and transportation networks over a planning horizon of a few years. The medium-term planning covers the production targets, inventories and distribution tasks between a few months to a year. Finally, the short-term planning deals with the allocation of production tasks in each process unit over a planning horizon of days to a few weeks. At the production level, the short-term planning is also referred to as scheduling (Shah and Ierapetritou, 2012).

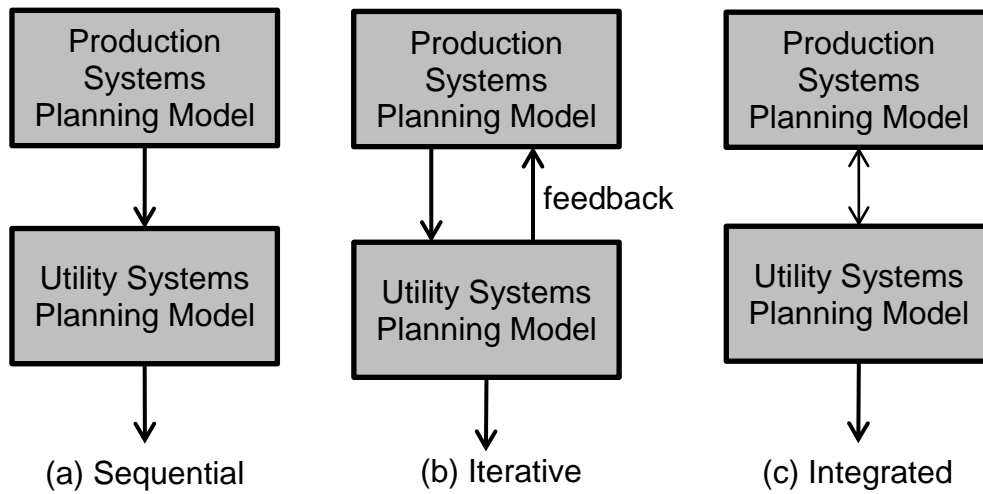


**Figure 1-4 Long-term, medium-term and short-term planning matrix (Maravelias and Sung, 2009)**

The most practical way to perform the operational planning in process industries is through the analysis of empirical tools such as planning cards and spreadsheet. The qualified planners executed the manual planning based on their observation and experiences. The main drawback of this empirical analysis is that the planning decisions will depend on the skills of experienced people (e.g., planners, engineers, and technicians). It will be difficult to make any decisions without acknowledge the information from them. As the complexity of the planning problem increases due to more production facilities and higher demand for products, many industrial companies have recognised the need for more systematic planning approaches in order to meet their production targets at low costs. The optimisation modelling and its solutions strategies can guarantee the best possible planning and significant cost savings through better utilisation of resources and energy.

The solution strategies for the planning and scheduling in process industries that were found in literature are exact methods and meta-heuristics methods. The exact methods are derived from mathematical optimisation including, mixed-integer programming (MIP), mixed-integer nonlinear programming (MINLP), or constraints programming (CP). These methods are the most appropriate methods on finding the best feasible solutions for the planning and scheduling problems. The meta-heuristics methods include the methods such as genetic algorithms (GA), simulated annealing (SA), and tabu search (TS). All meta-heuristics methods usually lack the capability of finding convergence and optimal solutions. However, they can be used to effectively improve particular solutions by performing local search based on appropriate neighbourhood relations. Therefore, Kallrath (2002) recommended the use of exact methods based on mathematical optimisation that are also known as state-of-the-art methods that can provide quantitative decisions and allow to cope successfully with complex planning problems.

In general, the planning and scheduling formulations are usually expressed as mixed-integer programming (MIP) model. Although the integrated model of production and utility systems can provide optimal planning solution, this integrated model often results in large MIP models that are computationally intractable to solve to optimality. One way to overcome this limitation is through the use of efficient solution strategies. The solution strategies for the integrated planning problems of production and utility systems in process industries can be classified into three categories as shown in Figure 1-5.



**Figure 1-5 Solution strategies for integrated planning problems of production and utility systems in process industries**

In decomposition method, the integrated planning problem is decomposed into a planning problem of production systems (i.e., master sub-problem) to determine production target and a planning problem of utility systems (i.e., slave sub-problem) to satisfy utility requirement by the production systems. The solution method is called sequential approach if the flow of information on production targets and other decisions are used as inputs to the planning problem of utility systems. If there is a feedback loop from the solutions on the planning of utility systems to the planning problem of production systems, then the method is an iterative approach. The solution strategy is called integrated approach if all information of production and utility systems is considered simultaneously. Some studies has shown that integrated approach to solve the planning problems of production and utility systems is better than that of the sequential approach in terms of cost savings and efficient utility generations (Agha et al., 2010; Zhao, Rong and Feng, 2014). Furthermore, iterative approach is the best approach to solve large MIP planning problems to obtain close optimality gap at faster computational performance than that of the integrated approach (Zhao, Rong and Feng, 2015). An excellent reviews of planning and scheduling problems,

modelling approaches and solutions methods can be found in Maravelias and Sung (2009).

In addition, the short-term planning should also consider maintenance planning to determine the time windows to perform maintenance on the process units, types of maintenance policies and the availability of maintenance resources. The main relation between operational and maintenance planning is on the requirement to monitor operational conditions of the process units and to perform necessary maintenance tasks in order to sustain the operational level of the overall process systems and restrain the units from entering critical states. The reviews that explore the integrated planning model of operational and maintenance aspects was discussed by Budai, Dekker and Nicolai (2008).

In general, the short-term planning can be further classified as the following: (i) operational planning; (ii) maintenance planning; and (iii) simultaneous operational and maintenance planning. The following sub-chapters explore the current status of operational, maintenance, and simultaneous operational and maintenance planning in terms of model formulations, objective functions and solution approaches.

#### **1.1.2.1 Operational Planning**

Early review on operational planning of production systems in process industries has been reported since the 1970s. Gelders (1981) recognised the need for integration of operational planning with other major functions such as inventory and distribution planning for effective overall production management. Glover, Jones, Karney, Klingman and Mote (1979) were among the first to consider integrated model for production, inventory and distribution planning that results to huge amount of cost savings in one of the major industrial companies. Moreover, Crama, Pochet and Wera (2001) added more discussions on operational planning approaches for production system such as raw materials planning, storage facilities planning, product blending and recipes management. Pinto, Joly and Moro (2000) implemented several types of operational planning approaches as discussed by Crama et al. (2001) that include inventory

management, oil blending and transport sequencing in refineries' oil pipelines to develop integrated model for short-term production and distribution schedule. Leung and Chan (2009) introduced resource utilisation constraints such as workforce level and machine utilisation for solving operational planning problem.

It needs to be highlighted that, the operational planning and scheduling model of batch production system is often more complicated in comparison to operational planning and scheduling of continuous production system due to additional operational constraints in the modelling framework to deal with multi-stage or multi-purpose processes. The batch production system can be generally classified as network and sequential processes. In the network process, batches of material are allowed for batch mixing or splitting. On the other hand, sequential process does not allow for batch splitting and mixing because the input of a batch can only be the output of another batch. Moreover, sequential process can be further classified as multi-stage process if the sequence of operation is the same for all products, and multi-purpose process if the sequence of operation is different among products. One of the pioneer work in the field of operational scheduling for batch processes was presented by Kondili, Pantelides and Sargent (1993). They presented material-based approach using a state-task network (STN) representation to develop a general framework for network batch processes. Meanwhile, Pinto and Grossmann (1998) proposed order-based approach to solve operational scheduling problem for sequential batch processes. They considered single-unit and multiple-unit assignment model. Many batch production systems consist of combination of sequential and network processes (e.g., recipe-based production). However, these works (Kondili, Pantelides and Sargent, 1993; Pinto and Grossmann, 1998) did not properly address the operational scheduling for simultaneous sequential and network batch processes. In order to address all operational scheduling problems for batch production system, Sundaramoorthy (2010) proposed a unified representation for sequential and network processes in batch production system. The special features of his proposed model relied on the characterisation of states and tasks of the batch subsystem, expression of sequential subsystem

using a material-based approach and enforcement of batch integrity in sequential subsystems. Recent works on integrated scheduling of multipurpose production system and CHP-based utility system is presented in Chapter 3.

In addition, Biel & Glock (2016) added that energy consumption in process industries should become part of operational planning problems by considering different energy aspects such as energy pricing policies and energy efficiency criteria that results to more advanced energy-efficient operational planning approaches. For example, Rong and Lahdelma (2007) and Mitra, Sun and Grossmann (2013) studied optimal schedule of industrial combined heat and power plant under time-sensitive electricity prices. Zhao, Ierapetritou and Rong (2016) formulated short-term planning model for ethylene plant that incorporates the operational constraints and energy utilisation. Salahi and Jafari (2016) addressed energy performance measures for optimal operational planning by incorporating various electricity pricing schemes.

There are also a number of works that highlight the current status of operational planning of utility systems in process industries. The first important works of operational planning of utility systems in 1990s was explored by Iyer and Grossmann (1997, 1998). They studied optimal multi-period operational planning of cogeneration system. A review on operational planning for CHP and cogeneration system from 1980s to 2000s was studied by Salgado and Pedrero (2008). There are also works that studied operational planning problems of other types of utility systems such as air separation units (Danyan Zhou et al., 2017) and steam power plants (Luo et al., 2013).

However, only a few works that dealt with operational planning of both production and utility systems as discussed in literature review sections (see Section 2.3.1, Section 3.3 and Section 4.3). The main reason mainly because the limitation on computational performance to solve such a complex integrated planning of production and utility systems without the method of effective solution strategies (e.g., decomposition approaches).

There is limited recent work on decomposition approaches to solve integrated planning problems of production and utility systems by considering all operational constraints of the overall process systems. The only work found is by Zhao, Rong and Feng (2015). They proposed solution strategy to decompose the integrated model of the two interconnected systems in refinery plants and iteratively solved the planning problem to further reduce the computational time. Therefore, this research work includes MIP-based decomposition strategy for solving scheduling problems of production and utility system (refer to Chapter 3).

Overall, all operational constraints of production and utility systems should be incorporated in the optimisation framework. In addition, complex operational planning problems should be solved through effective solution strategies.

### **1.1.2.2 Maintenance Planning**

In addition to operational planning, maintenance planning is also important to improve productivity and reliability of the overall processes in order to ensure excellent performance of the process units at minimum maintenance costs. Maintenance planning usually deals with the operational conditions of the process units to determine the best timing to perform maintenance tasks (e.g., cleaning, repairing and replacing), the available maintenance resources and the selection of different types of maintenance policies for the corresponding process units in the industrial plants. The common types of maintenance policies are time-based and condition-based maintenance. Excellent reviews on maintenance management can be found in Garg and Deshmukh (2006). The authors described the current issues related to maintenance management which include maintenance optimisation model, maintenance policies and maintenance scheduling. Additionally, Ahmad and Kamaruddin (2012) provided reviews on time-based and condition-based maintenance policies. Time-based maintenance policy is the preventive maintenance tasks that can be performed for the units at predefined time intervals. Meanwhile, condition-based maintenance policy is defined as preventive maintenance tasks by monitoring operating conditions of the units through various monitoring parameters such as vibration, process



temperature and noise levels. Different maintenance policies (i.e., fixed or flexible time-window cleaning tasks and condition-based cleaning tasks) have been applied in the modelling framework of this research as can be found in Chapter 2 to Chapter 4.

Early work in 1990s on maintenance planning of production system in process industry was introduced by Tan and Kramer (1997). The authors developed general optimisation framework for scheduled preventive maintenance planning of the chemical process plant with combined Monte Carlo simulation and genetic algorithm approach. Similar methods has been studied by Marseguerra and Zio (2000) to optimise maintenance and repair policies of an industrial production plant.

Moreover, maintenance planning of the production or utility system that consists of a network heat exchangers or compressors usually focuses on performance degradation and recovery model. Georgiadis et al. (2000) studied cleaning planning of heat exchanger networks under rapid fouling conditions in a dairy production system. Ishiyama et al. (2010) discussed cleaning planning of oil refinery preheat trains through fouling mitigation strategy. Pogiatzis et al. (2012) identified optimal cleaning schedule for heat exchangers subject to fouling and ageing. Labib and Alardhi (2008) studied preventive maintenance schedule for cogeneration plants by considering limitation on maintenance time window and number of workers. Rao and Naikan (2008) proposed online and offline cleaning for compressors of industrial gas turbine plant by monitoring the rate of fouling of compressors. More detailed literature review on the planning of cleaning operations has been discussed in Section 2.3.2.

The main objective of solving maintenance planning problems of either production or utility system is to maximise process profitability by finding the trade-off between process reliability and maintenance costs as discussed by Sachdeva et al. (2008). Therefore, it is an important step to consider both operational and maintenance constraints in the formulation of optimisation framework to find optimal operational and maintenance schedules.

### **1.1.2.3 Operational and Maintenance Planning**

The effective operational and maintenance planning plays one of the important roles for the efficient management of energy and resources in process industries. However, the operation of process units (e.g., production and utility units) may become inefficient due to poor interaction between operational and maintenance tasks. Inefficient process unit can possibly occur due to continuous operation with none or minimum maintenance tasks until reaching its maximum operational limits. At this point, potential damage and failure of the process unit may happen. The main reason of poor interaction between the operational and maintenance planning is due to the fact that both operational and maintenance planning are usually performed separately. For instance, operational planning model only focuses on the method to produce desired final products at maximum achievable production capacities without proper consideration to perform maintenance tasks on the process units. Similarly, maintenance planning model seldom considers customer's demands for products before performing maintenance tasks on the process units. These decisions will actually contribute to the problem of higher energy and resource utilisation due to inefficient operations of the overall process systems.

Despite the fact that operational or maintenance planning are the two planning areas that have received lots of research attention, the works on simultaneous operational and maintenance planning are still limited to either production systems or utility systems in the open literatures. There are few works on operational and maintenance planning for production systems considering availability of utilities (e.g., steam, cooling water, manpower) as presented by Goel, Grievink and Weijnen (2003). The optimisation framework for the design, operational and maintenance planning for multipurpose plant to determine optimal size and reliability of each process units was developed. Finally, the proposed optimisation-based approach on simultaneous operational and maintenance planning for production and utility systems are presented to show improved utilisation of energy and material resources than that of the traditional sequential approach (refer to Chapter 2 and Chapter 3).

Overall, the problems of operational and maintenance planning are always be interdependent especially in energy-intensive process industries. The optimisation-based approaches on simultaneous operational and maintenance planning should be readily available in open literatures. Furthermore, simulatenous operational and maintenance planning should be established as a new practice in industrial companies in order demonstrate major benefit from this approach such as optimal operational and maintenance schedules and overall cost savings.

### **1.1.3 Planning with Uncertainty**

The previous sub-chapters deal with deterministic models for the planning in process industries where all parameters are considered known. The planning problems under uncertainties can be crucial since many of parameters are not known exactly. Certain parameters such as availability of raw materials, prices, and products demand are often under unexpected deviations. The aim of solving the planning problems under uncertainty is to produce optimal and feasible schedules and to estimate future predictions of associated uncertain parameters based on the current states of the process system.

In general, uncertainty in a process industry can originate from many aspects based on the nature of the source of uncertainty. A classification of the source of uncertainty has been identified by Pistikopoulos (1995) as the following: (i) model-inherent uncertainty (e.g., physical properties, mass and heat transfer coefficients); (ii) process-inherent uncertainty (e.g., flow rate and temperature variations, fluctuation in stream quality); (iii) external uncertainty (e.g., product demands, fluctuations in energy prices); and (iv) discrete uncertainty (e.g., availability of process units). The following reviews explore comprehensive methods of optimisation modelling under uncertainty for process industries (Li and Ierapetritou, 2008; Sahinidis, 2004). There are two general approaches to deal with uncertainties namely known as reactive and proactive approach.

**Table 1-2 Main contributions on operational and maintenance planning in process industries**

Articles	Operational Planning	Maintenance Planning	Resources Management	Inventory Management	Production System	Utility System	Units performance	Uncertainty
Pinto et al. (2000)	√			√	√			
Vassiliadis & Pistikopoulos (2001)	√	√	√		√			√
Goel et al. (2003)	√	√	√	√	√	√	√	
Cassady & Kutanoglu (2005)	√	√	√		√		√	
Thorin et al. (2005)	√					√		
Labib & Alardhi (2008)		√	√			√	√	
Sitompul & Aghezzaf (2009)	√	√	√	√	√		√	√
Agha et al. (2009)	√		√	√	√	√		
Aghezzaf et al. (2010)	√			√	√			√
Agha et al. (2010)	√		√	√	√	√		
Castro et al. (2010)	√		√		√			√
Pandey et al. (2011)	√	√		√	√		√	
Neves et al. (2011)		√			√		√	
Kopanos et al. (2012)	√		√	√	√		√	
Mitra et al. (2012)	√			√	√	√		
Aretakis et al. (2012)		√				√	√	
Kopanos et al. (2013)	√			√		√	√	
Luo et al. (2013)	√	√		√		√	√	
Zhang et al. (2013)	√				√	√		
Castro et al. (2014)	√	√	√			√		
Zhao et al. (2014)	√				√	√		
Kopanos et al. (2015)	√	√	√	√		√	√	√
Lin et al. (2015)		√	√		√		√	
Liu et al. (2015)	√	√		√	√		√	
Tambe & Kulkarni (2015)	√	√	√		√		√	
Ardjmand et al. (2016)	√			√	√			√
Bindlish (2016)	√					√	√	
Zhao et al. (2016)	√		√	√	√		√	
Zulkafli & Kopanos (2016)	√	√	√	√	√	√	√	
Zulkafli & Kopanos (2017)	√	√	√	√	√	√	√	√

The reactive approach includes the methods of heuristic, rolling horizon and parametric programming. In reactive approach, the solution is implemented and updated in response to the presence of uncertainties and the new solutions are generated accordingly. The research work on the reactive planning under uncertainty that follows a rolling horizon modelling representation is presented in Chapter 2. The uncertain parameters in this study includes process-inherent uncertainty (e.g., level of inventory tanks), discrete uncertainty (e.g., startup and shutdown history of units), and external uncertainty (e.g., demands for products). Meanwhile, the proactive approach can generate solutions prior to the presence of uncertainties. The solutions of proactive approach remain feasible for all scenarios of uncertainties. The examples of the proactive approach is stochastic programming, fuzzy and robust model. In this research work, two-stage stochastic programming model is developed to solve planning problem under product demand uncertainty (refer to Chapter 4). Furthermore, the two-stage stochastic programming model follows a rolling horizon modelling representation that results to hybrid reactive-proactive planning approach as demonstrated in Section 4.6.2.

Table 1-2 shows the main contributions on operational and maintenance planning in process industries from year 2000 to year 2017 which include important planning aspects such as resource and inventory management, unit performances and uncertainties. The major observations are: (i) the resource and inventory management are mostly included in the operational planning of production systems; (ii) the unit performance model is usually applied in the maintenance planning of utility systems; and (iii) limited studies on simultaneous operational and maintenance planning under uncertainties for both production and utility systems.

To the best of my knowledge, there is none research that focuses on integrated planning of production and utility systems that includes all of these operational and maintenance aspects under process uncertainties. Therefore, two chapters of the PhD research are presented to highlight the applicability of the proposed optimisation framework to deal with uncertainty (refer to Chapter 2 and Chapter

4). In addition, several types of planning approaches (i.e., reactive, proactive and hybrid reactive-proactive approaches) is used to further enhance the proposed optimisation framework under uncertainty.

## **1.2 Motivation**

In 2015, it is estimated that maintenance and operating budget in process industries especially in hydrocarbon processing are expected to exceed more than \$345 billion worldwide (Romanow, DuBose and Blume, 2014). Approximately 80% of this cost is spent to restore chronic failure of machines, systems and human errors (Dhillon, 2002). The cost of maintenance as a fraction of operating budget can be as large as 40–50% for the mining industries (Murthy, Atrens and Eccleston, 2002) and 20–30% in the petrochemical industries (Tan and Kramer, 1997). The huge increase of operational and maintenance costs is due to the fact that the operational and maintenance planning are not considered simultaneously (refer to Section 1.1.2.1 and 1.1.2.2). In addition, the total costs will continue to rise to satisfy increasing demand for products especially in energy-intensive process industries.

In industrial practices, the operational and maintenance planning are usually performed separately most probably because of poor interaction between production department and maintenance department in the industrial companies (refer to Section 1.1.2.3). In addition, the planning problems of production and utility systems in process industries are typically solved sequentially. This sequential approach may not provide the best solutions in terms of feasible schedules and efficient utility generations (refer to Section 2.3.1).

The main challenges that has been identified on the development of optimization framework for the integrated operational and maintenance planning of production and utility systems are the following: (i) the inclusion of all operational and maintenance aspects; (ii) the identification of the source of uncertainties; (iii) the effective strategy to solve highly complicated planning problems at low computational performance; and (iv) improve energy supply and demand side by considering economic and environmental performances.

Therefore, these challenges are the major motivation of this PhD research that are realised through the development of the proposed optimization framework by considering all operational, maintenance and uncertainties aspects to solve integrated planning problems for production and utility systems (refer to Chapter 2, Chapter 3 and Chapter 4). The applicability of optimization framework is further enhanced with the method of decomposition strategy to find the best solutions at relatively low computational time (refer to Chapter 3). Additional work on the design and planning of energy supply chain network by using a unified modelling representation is presented to show the potentials of economic and emissions reduction. Furthermore, the proposed modelling representation can also specifically address the planning problems of material and energy supply chain operations in process industries (refer to Chapter 5).

### **1.3 Aim and Objectives**

The aim of this research is to show the applicability and major benefits of the integrated planning of production and utility systems, such as efficient energy and material resources utilisation, emission reduction and overall cost reduction. In order to meet this aim, the following objectives have been established:

- (a) Objective 1: to identify the current status of operational and maintenance planning for the process industry.
- (b) Objective 2: to develop optimal operational and cleaning planning optimisation-based approach for the process industry.
- (c) Objective 3: to further enhance the developed optimisation-based approach by considering process uncertainties.
- (d) Objective 4: to enhance the applicability and the efficiency of the production and cleaning planning by integrating the optimisation-based approach with decomposition strategy.
- (e) Objective 5: to demonstrate the benefits of the simultaneous operational and cleaning planning of production and utility systems through comprehensive analysis.

## 1.4 Structure of PhD Thesis

This thesis consists of eight chapters that have been organised as shown in Figure 1-6. The detailed information of each chapter is discussed as follows:

Chapter 1 focuses on research background of the thesis which includes overall reviews of process industries and current status of the planning approaches in process industries. The planning with uncertainties is briefly discussed. The motivation, aim and objective, structure of PhD thesis and dissemination from the PhD thesis are properly described.

Chapter 2 presents a general rolling horizon optimisation framework for the integrated condition-based operational and maintenance planning of production and utility systems. Three case studies are presented in this chapter. Case study 1 considers flexible time-window offline cleaning tasks for utility and production units. Case study 2 studies a condition-based cleaning tasks for utility units and a flexible time-window cleaning tasks for production units. In case study 3, the reactive planning problem of utility and production systems through rolling horizon modelling representation is considered. The cost comparison between integrated and sequential rolling horizon approaches is analysed. Chapter 2 is derived from a published paper in Applied Energy (Zulkafli and Kopanos, 2016) and in Journal of Cleaner Production (Zulkafli and Kopanos, 2017).

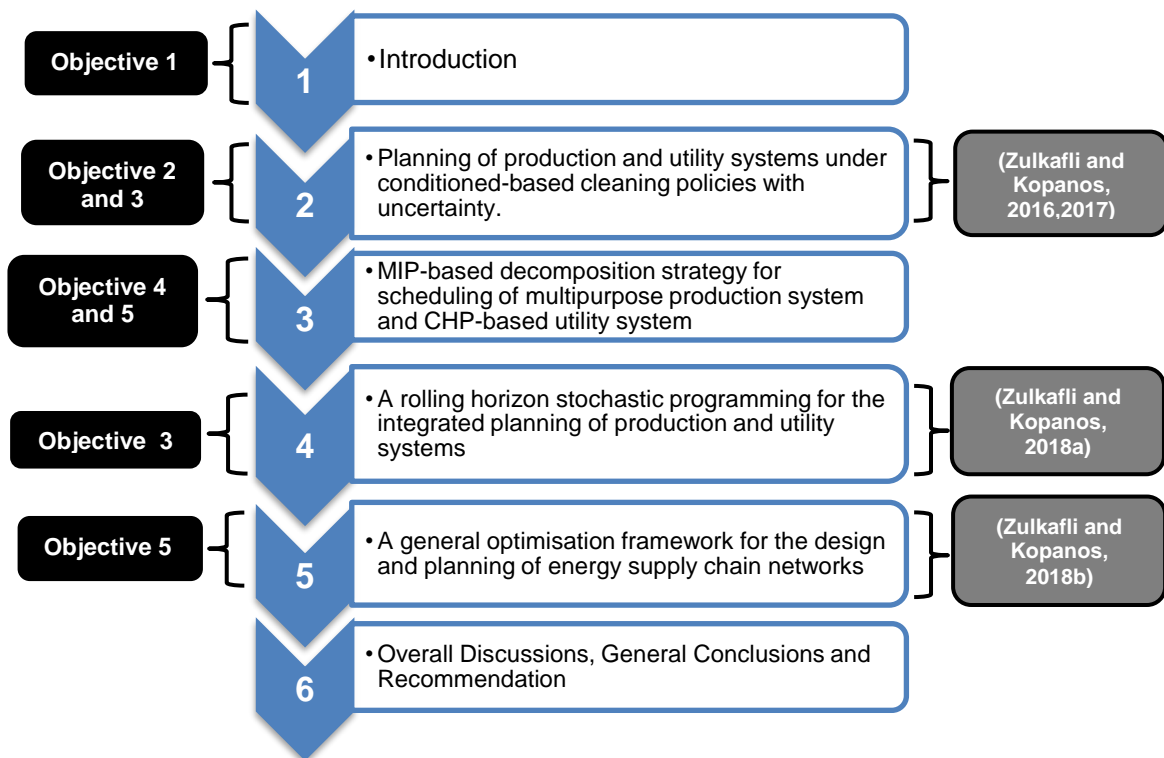
Chapter 3 proposes MIP-based decomposition strategy for scheduling of multistage production system and combined heat and power. The computational experiments are conducted to demonstrate the features of the proposed decomposition strategy. The effect of emissions caps on the integrated planning approach is briefly discussed.

Chapter 4 studies about a rolling horizon stochastic programming approach for the integrated planning. There are two case studies in this chapter. Case study 1 presents integrated planning via stochastic programming and case study 2 discusses about integrated planning via a rolling horizon stochastic programming approach. This chapter has been recently published in Chemical Engineering Research and Design (Zulkafli and Kopanos, 2018a).



Chapter 5 presents a general optimization framework for the design and planning of material and energy supply chain networks. A unified modelling representation for effective supply chain management under economic and environmental analysis is considered. Chapter 6 is the latest published paper in Chemical Engineering Research and Design (Zulkafli and Kopanos, 2018b).

Chapter 6 provides detailed overall discussions and novelty to evaluate important connections between research objectives and research works as discussed on each following chapter (i.e., Chapter 2 to Chapter 5). In addition, general conclusions based on the summary of the main research findings and recommendation for future development in this research is summarized in this chapter.



**Figure 1-6 Structure of PhD thesis and corresponding list of published work**

## 1.5 Dissemination from the PhD Thesis

The list of publications and presentation from the PhD research are given below. The dissemination from the PhD thesis is divided into the following categories:

### **1.5.1 Peer-Reviewed Journal Publications**

Zulkafli, N.I. and Kopanos, G.M. (2018a) 'A rolling-horizon stochastic programming approach for the integrated planning of production and utility systems', *Chemical Engineering Research and Design*, 139, pp. 224–247.

Zulkafli, N.I. and Kopanos, G.M. (2018b) 'A general optimization framework for the design and planning of energy supply chain networks: Techno-economic and environmental analysis', *Chemical Engineering Research and Design*, 131, pp. 214–233.

Zulkafli, N.I. and Kopanos, G.M. (2017) 'Integrated condition-based planning of production and utility systems under uncertainty', *Journal of Cleaner Production*, 167, pp. 776–805.

Zulkafli, N.I. and Kopanos, G.M. (2016) 'Planning of production and utility systems under unit performance degradation and alternative resource-constrained cleaning policies', *Applied Energy*, 183, pp. 577–602.

### **1.5.2 Conference and Poster Presentation**

The list of conference and poster presentation throughout the PhD studies is shown in Table 1-3.

**Table 1-3 List of conference and poster presentation**

<b>Conferences</b>	<b>Location</b>	<b>Date</b>	<b>Status</b>
Newton Fund Al-Farabi Researcher Links UK- Kazakhstan Workshop on “Low-Carbon Energy Future: Efficient Management of Resources and Energy	Astana, Kazakhstan	26 <sup>th</sup> – 29 <sup>th</sup> September 2016	Poster presentation
The 6th International Symposium on Advanced Control of Industrial Processes	Taipei, Taiwan	28 <sup>th</sup> May – 31 <sup>st</sup> May 2017	Oral presentation
PSE@ Research Day UK	London, UK	27 <sup>th</sup> June 2017	Oral presentation
European Symposium on Computer-Aided Process Engineering 27	Barcelona, Spain	1 <sup>st</sup> – 5 <sup>th</sup> October 2017	Keynotes Lecture

### **1.5.3 Conference Publications**

Zulkafli, N.I. and Kopanos, G.M. (2017) ‘Simultaneous planning of production and utility systems under performance degradation’, *2017 6th International Symposium on Advanced Control of Industrial Processes (AdCONIP)*. Taipei: IEEE, pp. 113–118.

Zulkafli, N.I. and Kopanos, G.M. (2017) ‘Rolling Horizon Condition-based Planning of Production and Utility Systems in Process Industries’, in Antonio Espuña, Moisès Graells, L. P. (ed.) *Computer Aided Chemical Engineering*. Elsevier, pp. 1333–1338.

## 2 PLANNING OF PRODUCTION AND UTILITY SYSTEMS UNDER CONDITION-BASED CLEANING POLICIES WITH UNCERTAINTY <sup>a,b</sup>

### 2.1 Abstract

A general rolling horizon optimisation framework for the integrated condition-based operational and maintenance planning of production and utility systems in process industries is presented. In brief, the proposed optimisation framework considers for the production and utility units: (i) improved unit performance degradation and recovery models that depend on both the cumulative time of operation and the unit operating levels deviation of units; (ii) modified operating capacities under online cleaning periods; (iii) different types of cleaning tasks (flexible time-window and online or offline condition-based); (iv) alternative options for offline cleaning tasks; (v) limited availability of cleaning resources; (vi) the initial state of the overall system at the beginning of each planning horizon; and (vii) terminal constraints for the rolling horizon problem. The case studies solved show that when compared to solutions obtained by sequential approaches the proposed integrated approach provides significantly better solutions in terms of total costs (reduction from 5%-32%), and especially in cost terms related to utility units operation, energy consumption, cleaning and startup/shutdown operations. Unnecessary cleanings and purchases of resources can be avoided by the proposed integrated approach. Overall, the significant reduction in total costs is a direct result of the enhanced energy efficiency of the overall system through the efficient generation and use of energy, the improved utilisation of energy and material resources resulting in a more sustainable and cleaner production practices.

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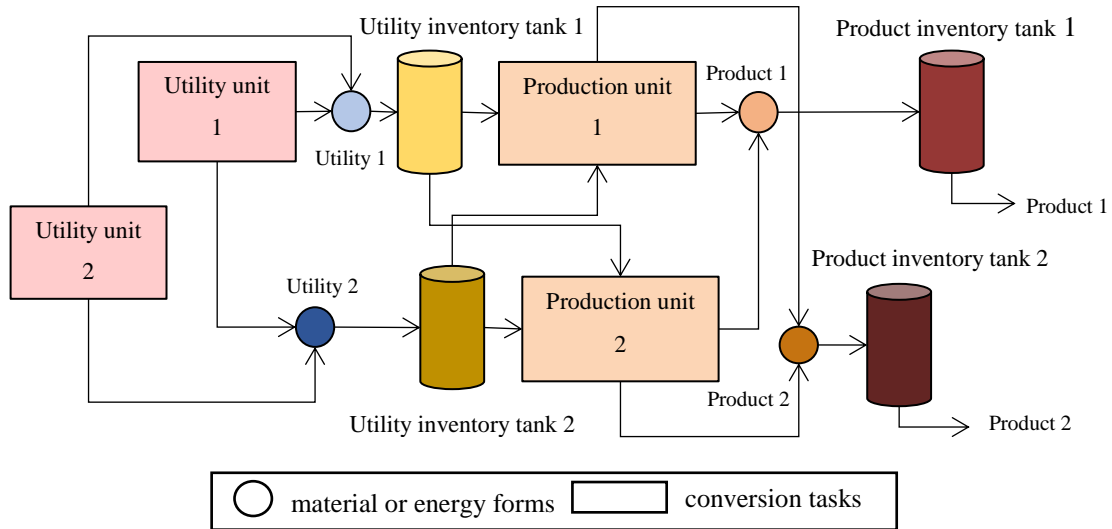
<sup>a</sup> Zulkafli, N.I. and Kopanos, G.M. (2016) 'Planning of production and utility systems under unit performance degradation and alternative resource-constrained cleaning policies', *Applied Energy*, 183, pp. 577–602.

<sup>b</sup> Zulkafli, N.I. and Kopanos, G.M. (2017) 'Integrated condition-based planning of production and utility systems under uncertainty', *Journal of Cleaner Production*, 167, pp. 776–805.

## 2.2 Introduction

One of the main goals of any process industry is to generate maximum revenues at low costs by maintaining high production levels in order to satisfy the demand for products. A means for achieving this is by following a plant-wide approach through the integrated management of operational and maintenance tasks in the overall process system (Zulkafli and Kopanos, 2016).

Major industrial facilities consist of interconnected production and utility systems. Figure 2-1 displays a representative layout of production and utility systems for a process industry. Under this plant layout, the production system produces desired products from raw materials that may undergo several production processes, such as reactions or separations. These main production processes require large amounts of different utilities, such as power, steam, compressed air, industrial gases or water. Especially, energy-intensive process industries have an onsite utility system that generates the major utilities required by the main production system. Combined heat and power units, gas or steam turbines, compressors, and boilers are examples of onsite utility systems. The raw materials of the utility system can be any type of fuel or other resource, such as atmospheric air or water. These materials undergo a conversion process in utility units to generate the desired utilities. Depending on the type of utility, chemical or physical conversion could take place in a utility unit (e.g., combustion or compression). Then, the generated utilities are supplied to the production system for its own operation and the production of intermediate or final products. Excessive amounts of utilities can be stored in buffer tanks (e.g., hot water), be recycled (e.g., steam), or in some cases be released to the environment (e.g., exhaust heat). Some utilities may be acquired from external sources under an associated cost, if the onsite utility system cannot meet the needs of the production system (e.g., electricity from the power grid). Production and utility units may operate in parallel or in series depending on the overall process of their corresponding production or utility system. Final products or utilities can be stored in dedicated inventory tanks or directly satisfy the demand for products or the utility requirements of the production system, respectively.



**Figure 2-1 Representative layout for the interaction of production and utility systems**

In addition to the above, modern process plants consist of complex operating equipment that require maintenance to perform its required function in a timely manner to avoid equipment damage and inefficient use. Effective maintenance policies can sustain the operational level, reduce operating costs, and restrain the equipment and the overall system from entering hazardous states. The cleaning of production or utility equipment that is subject to performance degradation is one of the major maintenance actions in process industries. The purpose of this cleaning is to recover the performance (efficiency) of the corresponding equipment and decrease energy consumption over its operation. Thus, it is essential to consider condition-based maintenance policies for the equipment of a process plant to increase its overall energy efficiency, operability and stability (Xenos et al., 2016). To do this, performance degradation and recovery models need to be derived for each equipment and alternative maintenance policies need to be considered (e.g., online or offline cleaning).

It is clear from the above discussion that a systematic approach is needed for addressing the plant-wide management and planning of a process industry. In addition, none of the above works on integrated planning of production and utility

systems studied about condition-based and resource-focused approaches for operational and maintenance planning and follows a rolling horizon modelling representation in order to readily deal with various types of uncertainty. For this reason, this study focuses on the integrated planning of production and utility systems, where both systems are optimised simultaneously. The novelty of the proposed method follows a plant-wide condition-based approach for maintenance actions and a plant-wide resource-focused approach towards the improved utilisation of all process-related major resources (plant-wide resource efficiency). This integrated approach is a key step towards the transformation of current process industries to smart process industries, following the Internet-of-Things revolution, where all operations are performed to achieve substantially enhanced energy, sustainability, environmental and economic performance.

This is the first work that deals with the problem under consideration and provides such an integrated framework for its solution. Of great importance is also the fact that in this study comprehensive comparisons are made between the solutions obtained following the proposed integrated approach and the traditional sequential approach, demonstrating clearly the important benefits of the proposed approach over its sequential counterpart. Overall, the proposed integrated method follows a whole-system approach that addresses the efficient energy generation, use and consumption (i.e., production and utility units under performance degradation and recovery), improved material handling (i.e., resource-constrained cleaning policies), and integrated management of energy and material resources in dynamic environments (i.e., integrated approach under uncertainties) towards a cleaner and sustainable production in process industries.

The chapter is laid out as follows. Section 2.3 provides a brief literature review on the integrated planning of production and utility systems. In Section 2.4, the problem statement of the subject study under question is formally defined. The proposed optimisation framework is then presented in Section 2.5, followed by the description and the discussion of the results of all case studies in Sections 2.6. Finally, concluding remark is provided in Section 2.7.

## **2.3 Literature Review**

### **2.3.1 Planning of Production and Utility System**

Most process industries, and especially the most energy-intensive, have installed onsite a utility system for meeting the utility requirements of the principal production system. A sequential approach is typically used for the planning of utility and production systems, as is explained below. First, the planning of the production system is performed considering simply upper bounds on the availability of utilities. Once the production plan is derived, the utility needs of the production are known. This information is then used for obtaining the operational planning of the utility system. This sequential approach provides suboptimal solutions (mainly in terms of energy efficiency and costs) because the two interconnected systems are not optimised at the same time. For this reason, this work focuses on the simultaneous planning of utility and production systems. A brief literature review on the subject follows.

Most previous studies have addressed either the planning of production systems (Kopanos, Puigjaner and Georgiadis, 2011; Kopanos, Puigjaner and Maravelias, 2011; Xie et al., 2016; Zhao, Ierapetritou and Rong, 2016) or the planning of utility systems independently (Aguilar et al., 2007; Kopanos and Pistikopoulos, 2014; Thorin, Brand and Weber, 2005). There are few works that dealt with the simultaneous planning of utility and production systems. For example, Agha et al. (2010) presented a Resource-Task Network based mathematical model for the simultaneous planning of a manufacturing and a combined heat and power plant. The results of their case studies demonstrated clearly that this integrated approach reduces significantly the energy costs and the emissions of greenhouse gases compared to the traditional sequential approach. In another study, Zhang et al. (2013) developed a mixed integer nonlinear programming model that includes the heat integration of the process plant, the optimisation of the utility system and coupling equations for the site-scale steam integration. Zhao, Rong and Feng (2014) presented mathematical models for the simultaneous planning of a refinery and its onsite utility system. The results of all the above works



showed that the integrated planning of utility and production systems could result in significant energy savings, emissions and overall costs reductions.

### **2.3.2 Planning of Cleaning Operations**

The cleaning of specific equipment that are characterised by performance degradation (e.g., due to fouling), such as compressors and heat exchangers, is one of the major maintenance actions in process industry (Alle, Papageorgiou and Pinto, 2004; Georgiadis and Papageorgiou, 2000; Pogiatis et al., 2012). The purpose of these cleaning operations is to recover the performance (efficiency) of equipment and that way decreases their energy consumption or increases the energy savings over the operation of the equipment. There are two main cleaning strategies to deal with equipment performance degradation, namely online and offline cleaning. Online cleaning tasks take place without interrupting the operating status of the equipment and recover partially the performance of the equipment. An example of online cleaning task is the injection of a cleaning solution in the equipment while it is still under operation. Offline cleaning tasks can be performed only when the equipment is closed and it is generally assumed that they can recover the full performance of the equipment. The duration of offline cleaning tasks can be considerably higher than that of online tasks, because during offline cleaning other supplementary maintenance tasks, such as mechanical and electrical inspections, take place. The interested reader could be referred to the works of Pattanayak et al. (2015) and Tian et al. (2016) for more detailed discussion on the cleaning of equipment.

A few studies studied different types of cleaning tasks, resource allocation, cleaning duration and costs. For example, Nguyen et al. (2008) studied the trade-off between the number of workers, cleaning cost and economic losses. They show that for limited available cleaning resources, the cleaning tasks did not perform on time and economic loss occurred. While for excessive available cleaning resources, the maintenance tasks can be done on time but the total cleaning cost may become unnecessary high. Kopanos et al. (2015) presented an optimisation framework for the planning of a network of compressors considering limitations on the number of compressors that could be under

maintenance simultaneously. Do et al. (2015) studied a multi-component system with limited maintenance team and they showed that the minimum number of available resources can be obtained by minimizing the maintenance cost. Most of the works on the planning of cleaning tasks did not consider resources limits for the cleaning operations (i.e., selection of alternative cleaning options, maximum availability of cleaning resources).

## 2.4 Problem Statement

This work focuses on the detailed condition-based operational and cleaning planning of production and utility systems under alternative resource-constrained cleaning policies, through the consideration of performance degradation and recovery for utility and production units. This integrated planning problem is formally defined in terms of the following items:

- A given planning horizon divided into a number of equally-length time periods  $t \in T$ .
- A set of energy or material resources  $e \in E$  that are classified to final product ( $e \in E^{PR}$ ) and utility resources ( $e \in E^{UT}$ ). The final products have known demand profiles  $\zeta_{(e,t)}$ .
- A set of units  $i \in I$  that could produce a number of resources  $e \in E_i$ . These units are categorised to utility ( $i \in UT_i$ ) and production ( $i \in PR_i$ ) units. Maximum (minimum) operating levels  $\kappa_{(i,t)}^{\max}$  ( $\kappa_{(i,t)}^{\min}$ ) for utility units and production levels  $\bar{\kappa}_{(i,e,t)}^{\max}$  ( $\bar{\kappa}_{(i,e,t)}^{\min}$ ) for production units are known. For the units that have a maximum runtime ( $i \in MR_i$ ), the maximum runtime ( $o_i$ ) after its last startup is defined. For every unit that is subject to startup and shutdown actions ( $i \in I^{SF}$ ), the costs for startup ( $\phi_{(i,t)}^S$ ) and shutdown ( $\phi_{(i,t)}^F$ ) are also given. For any unit that is subject to minimum runtime and shutdown time restrictions (i.e.,  $i \in I^{S-\min}$  and  $i \in I^{F-\min}$ , respectively), the minimum runtime after its last startup  $\omega_i$  and the minimum idle time after its last shutdown  $\psi_i$  are also defined.

- A set of resource-dedicated inventory tanks  $i \in IT_e$  that can receive resources from units  $i \in ZI_i^+$  and send resources to units  $i \in ZI_i^-$ . The inventory tanks have a given maximum (minimum): inventory tank level  $\beta_{(e,i)}^{\max}$  ( $\beta_{(e,i)}^{\min}$ ), inlet resource flow  $\beta_{(e,i,t)}^{-,\max}$  ( $\beta_{(e,i,t)}^{+,\min}$ ), and outlet utility resource flow  $\beta_{(e,i,t)}^{-,\max}$  ( $\beta_{(e,i,t)}^{-,\min}$ ). Initial inventory tank levels  $\tilde{\beta}_{(e,i)}$  and losses coefficients  $\beta_i^{\text{loss}}$  are also given.
- Different cleaning policies for the units are considered. In particular, a unit could be subject to: (i) flexible time-window offline cleaning ( $i \in FM_i$ ) with a given earliest  $\tau_i^{es}$  and latest  $\tau_i^{ls}$  starting time, (ii) in-progress offline cleaning carried over from the previous planning horizon ( $i \in DM_i$ ), or (iii) condition-based cleaning ( $i \in CB_i$ ) with known performance degradation rates. Two types of condition-based cleaning tasks are considered, namely: online cleaning tasks ( $CB_i^{on}$ ) with given recovery factors  $\rho_i^{rec}$ , and offline cleaning tasks ( $CB_i^{off}$ ).
- A set of alternative cleaning tasks options  $q \in Q_i$  for each unit that is subject to flexible time-window cleaning ( $i \in FM_i$ ) or offline condition-based cleaning ( $i \in CB_i^{off}$ ). The cleaning tasks options are characterised by different durations  $v_{(i,q)}$ , cleaning resource requirements  $g_{(i,q)}^{off}$ , and associated cleaning costs  $\phi_{(i,q,t)}^{off}$ .
- For every production unit  $i \in I_e^{PR}$ , fixed and variable utility requirements for the production of final products are given ( $\bar{\alpha}_{(i,e,e')}$  and  $\alpha_{(i,e,e')}$ , respectively).
- Given variable and fixed operating costs for production and utility units,  $\phi_{(i,e,t)}^{PR,op-var}$  and  $\phi_{(i,e,t)}^{PR,op-fix}$ , and  $\phi_{(i,t)}^{UT,op-var}$  and  $\phi_{(i,t)}^{UT,op-fix}$ , respectively.
- Given purchase prices for acquiring utility and product resources from external sources,  $\phi_{(e,i,t)}^{UT,ex}$  and  $\phi_{(e,t)}^{PR,ex}$  respectively.
- A given time-varying energy price profile  $\phi_{(i,t)}^{pw}$ .

Some additional considerations of the problem under study are the following: (i) the demands for final products should be fully satisfied; and (ii) there is a limited amount of available resources for cleaning tasks per time period.

For every time period, the key decisions to be made by the optimisation model are:

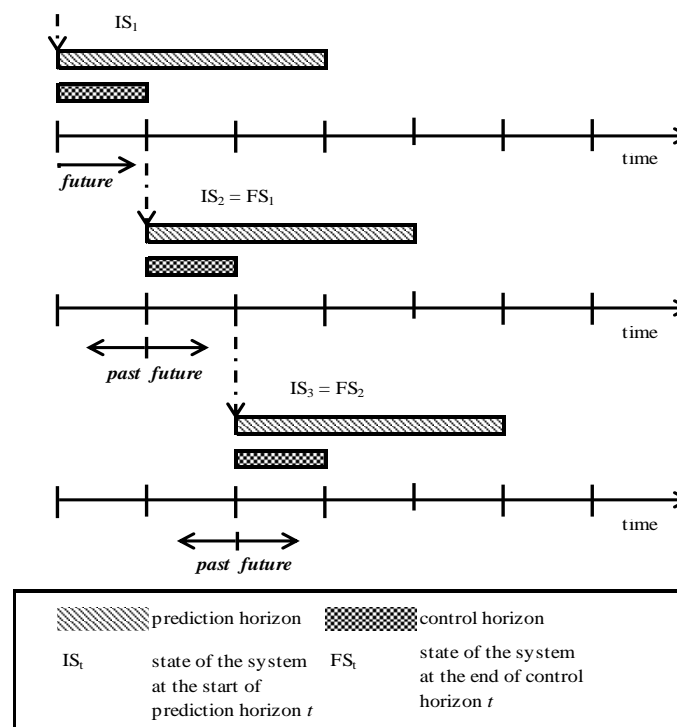
- the operational status for each production and utility unit (i.e., startup, shutdown, in operation, idle, under cleaning);
- the operating level for each production and utility unit;
- the inventory level for each inventory tank of utility and product resources;
- the utility requirements of each production unit; and
- the selection of the timing and the types of the cleaning tasks to be performed in each production and utility unit.

And all these with the goal to minimise the cost of the overall process system which includes:

- fixed and variable operating costs for production and utility units;
- startup and shutdown costs for production and utility units;
- extra energy costs due to performance degradation for production and utility units;
- cleaning costs for production and utility units; and
- penalties or costs for acquiring utility and product resources from external sources.

## 2.5 Optimisation Framework

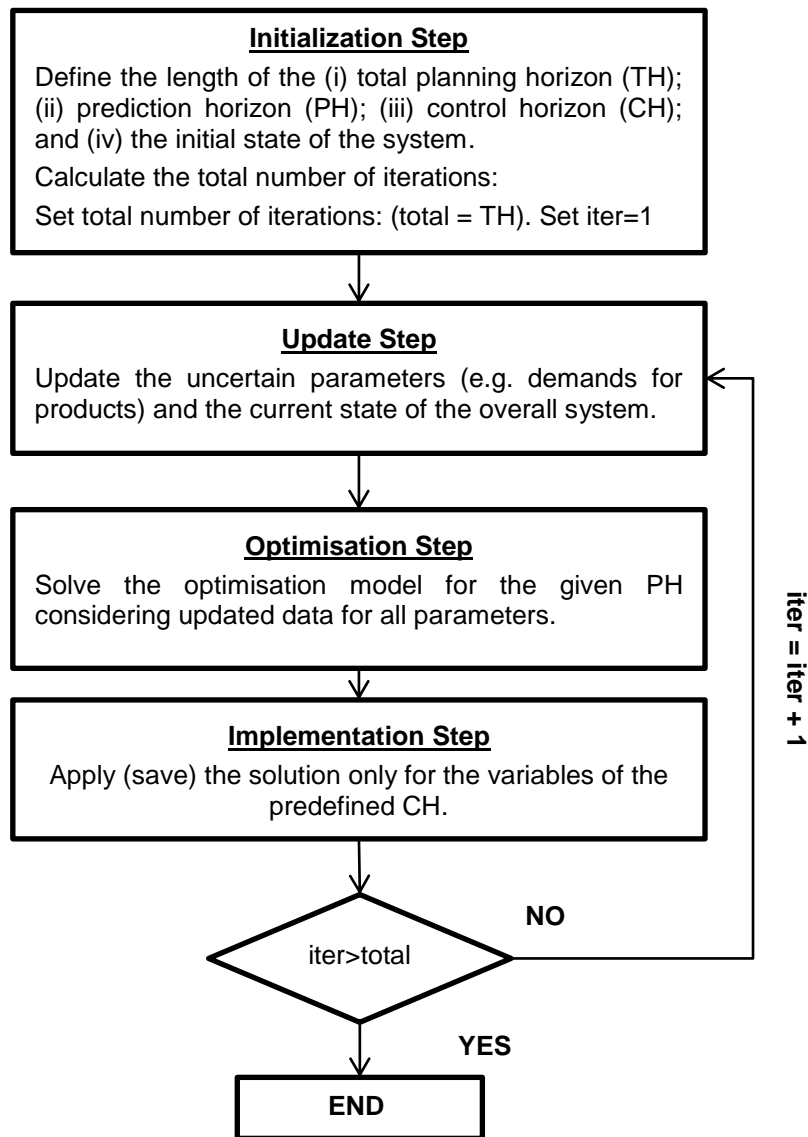
In this section, a linear mixed integer programming model is presented for the integrated planning problem considered in this study. The proposed mathematical model follows a rolling horizon modelling representation in order to readily deal with various types of uncertainty, such as fluctuations on the demand for final products, unit breakdowns, variations of cost terms, or data inaccuracies. In brief, in the rolling horizon scheme, a planning problem is solved for a certain length of time horizon (i.e., prediction horizon), and then the solution for a part of that time horizon (i.e., control horizon) is executed (typically for the first time period of the prediction horizon). After each iteration, a new planning problem is solved by moving forward the time horizon by the length of the control horizon considered.



**Figure 2-2 A representative rolling horizon example for reactive planning**

Figure 2-2 displays a representative rolling horizon example for the reactive planning problem described above. In a rolling horizon framework, the state of the overall system and the uncertain parameters of the problem are updated

before each iteration. The main parameters that need to be updated are: (i) the level of every inventory tank; (ii) the cumulative time of operation per unit; (iii) the deviation of the operating level per unit; (iv) the current operating status of each unit; (v) the startup and shutdown history of units; (vi) the online cleaning history of units; and (vii) the demands for products.



**Figure 2-3 Reactive planning method via rolling horizon**

Figure 2-3 shows a schematic representative of the steps of the proposed reactive planning method. A description of the proposed optimisation framework follows.

### 2.5.1 Startup and Shutdown Actions

In order to model the major operational status (i.e., in operation, idle, startup, or shutdown) of production and utility units, the following set of binary variables is introduced:

$$X_{(i,t)} = \begin{cases} 1 & \text{if unit } i \text{ is operating during time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$S_{(i,t)} = \begin{cases} 1 & \text{if unit } i \text{ starts up at the beginning of time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$F_{(i,t)} = \begin{cases} 1 & \text{if unit } i \text{ shuts down at the beginning of time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

For the sake of clarity, an illustrative example of the major optimisation variables is displayed in Figure 2-4. This figure shows the timing of a unit during operations, shutdown and under online or offline cleanings.

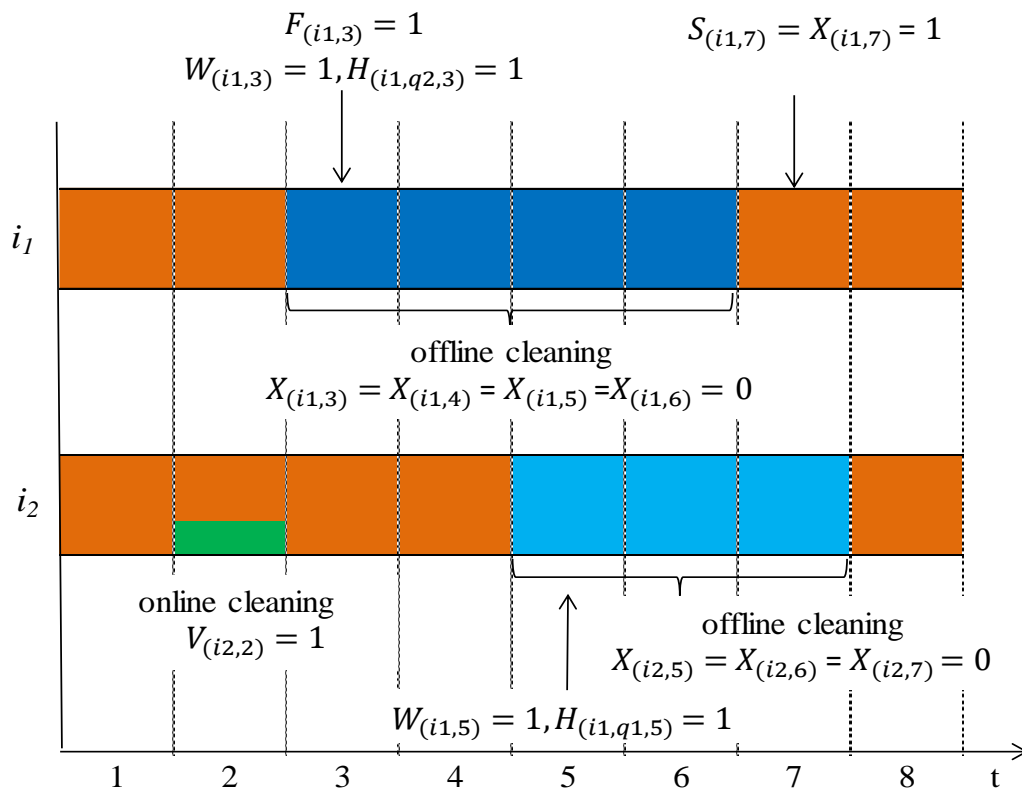


Figure 2-4 Illustrative example for the main optimisation variables

The operational status of each unit is then modelled according to:

$$S_{(i,t)} - F_{(i,t)} = X_{(i,t)} - \tilde{\chi}_i \quad \forall i \in I, t \in T : t = 1 \quad (2-1)$$

$$S_{(i,t)} - F_{(i,t)} = X_{(i,t)} - X_{(i,t-1)} \quad \forall i \in I, t \in T : t > 1$$

$$S_{(i,t)} + F_{(i,t)} \leq 1 \quad \forall i \in I, t \in T \quad (2-2)$$

The first two sets of constraints relate the startup and shutdown actions with the operating binary variables, while the last set of constraints ensure that no startup and shutdown action can occur simultaneously.

For instance, according to constraints (2-1), if a utility unit has not been operating in the previous time period but operates in the current time period, then a startup takes place (i.e.,  $S_{(i,t)} = 1$  and  $F_{(i,t)} = 0$ ). Parameter  $\tilde{\chi}_i$  denotes the operating status of utility unit  $i$  just before the start of the planning horizon. If the utility unit  $i$  has been operating just before the start of planning horizon, then  $\tilde{\chi}_i = 1$ , otherwise it is zero. Constraints (2-2) exclude the simultaneous realization of a startup and a shutdown action. If startup and shutdown costs are included in the objective function, constraints (2-2) could be excluded from the optimisation model, since their corresponding values will tend to zero.

The minimum runtime  $\omega_i$  and shutdown time  $\psi_i$  for any unit subject to minimum runtime or shutdown restriction are modelled by constraints (2-3) and (2-4), respectively.

$$X_{(i,t)} \geq \sum_{t'=\max\{1,t-\omega_i+1\}}^t S_{(i,t')} \quad \forall i \in I^{S-min}, t \in T : \omega_i > 1 \quad (2-3)$$

$$X_{(i,t)} = 1 \quad \forall i \in I^{S-min}, t = 1, \dots, (\omega_i - \tilde{\omega}_i) : 0 < \tilde{\omega}_i < \omega_i$$

$$1 - X_{(i,t)} \geq \sum_{t'=\max\{1,t-\psi_i+1\}}^t F_{(i,t')} \quad \forall i \in I^{F-min}, t \in T : \psi_i > 1 \quad (2-4)$$

$$X_{(i,t)} = 0 \quad \forall i \in I^{F-min}, t = 1, \dots, (\psi_i - \tilde{\psi}_i) : 0 < \tilde{\psi}_i < \psi_i$$

Parameters  $\tilde{\omega}_i$  ( $\tilde{\psi}_i$ ) describe the initial state (e.g., age in time periods) of each unit with respect to its total number of consecutive operating (idle) periods since



its last startup (shutdown) at the beginning of the current planning horizon. Constraints (2-3) and (2-4) are needed only if the minimum runtime  $\omega_i$  or shutdown time  $\psi_i$  of a unit is greater than a single time period, respectively.

Generally speaking, a maximum runtime ( $o_i$ ) may be imposed for units  $i \in MR_i$  that do not follow a more detailed performance-based cleaning planning, according to:

$$\begin{aligned} \sum_{t'=\max\{1,t-o_i\}}^t X_{(i,t')} &\leq o_i & \forall i \in MR_i, t \in T \\ \sum_{t'=\max\{1,t-(o_i-\tilde{\omega}_i)\}}^t X_{(i,t')} &\leq (o_i - \tilde{\omega}_i) & \forall i \in MR_i, t = (o_i - \tilde{\omega}_i + 1) : \tilde{\omega} > 1 \end{aligned} \quad (2-5)$$

## 2.5.2 Cleaning Tasks

As discussed in Problem statement, the different unit cleaning policies considered are: (i) flexible time-window offline cleaning ( $i \in FM_i$ ), (ii) in-progress offline cleaning carried over from the previous planning horizon ( $i \in DM_i$ ), or (iii) condition-based cleaning ( $i \in CB_i$ ). Online cleaning ( $CB_i^{on}$ ) and offline cleaning tasks ( $CB_i^{off}$ ) are considered for the condition-based cleaning. The following binary variables are defined to model these cleaning tasks.

$$\begin{aligned} H_{(i,q,t)} &= \begin{cases} 1 & \text{if a cleaning task option } q \text{ for } i \in (CB_i^{off} \cup FM_i) \text{ begins at the start of time period } t, \\ 0 & \text{otherwise.} \end{cases} \\ W_{(i,t)} &= \begin{cases} 1 & \text{if an offline cleaning task for } i \in (CB_i^{off} \cup FM_i) \text{ begins at the start of time period } t, \\ 0 & \text{otherwise.} \end{cases} \\ V_{(i,t)} &= \begin{cases} 1 & \text{if an online cleaning task for } i \in (CB_i^{on} \cap UT_i) \text{ takes place in time period } t, \\ 0 & \text{otherwise.} \end{cases} \\ V_{(i,e,t)}^{PR} &= \begin{cases} 1 & \text{if an online cleaning task for } i \in (CB_i^{on} \cap PR_i) \text{ that produces product } e \in E_i \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases} \end{aligned}$$

### 2.5.2.1 In-Progress Offline Cleaning Tasks

At the beginning of the planning horizon, there may be some in-progress unfinished offline cleaning tasks for some units ( $i \in DM_i$ ) which are carried over

from the previous planning horizon. These cleaning tasks are modelled according to:

$$X_{(i,t)} = 0 \quad \forall i \in DM_i, t \in T : \tilde{\eta}_{(i,t)} > 0 \quad (2-6)$$

Parameters  $\tilde{\eta}_{(i,t)}$  represent the known cleaning resources requirements of units that are under in-progress offline cleaning at the beginning of the planning horizon of interest.

### 2.5.2.2 Flexible Time-Window Offline Cleaning Tasks

In general, there may be alternative options for these offline cleaning tasks. And as such, one cleaning task option need to start within the given time window  $t = [\tau_i^{es}, \tau_i^{ls}]$ , as given by:

$$\sum_{q \in Q_i} \sum_{t=\tau_i^{es}}^{\tau_i^{ls}} H_{(i,q,t)} = 1 \quad \forall i \in FM_i \quad (2-7)$$

Observe that such multiple cleaning tasks can be modelled for a unit by providing different non-overlapping time windows, if needed.

### 2.5.2.3 Condition-Based Online Cleaning Tasks

In any given time period, a unit could be under online cleaning only if the unit is under operation during this period, as modelled by:

$$V_{(i,t)} \leq X_{(i,t)} \quad \forall i \in CB_i^{on}, t \in T \quad (2-8)$$

In practice very frequent online cleaning may affect negatively the condition and operation of a unit. For this reason, the proposed approach considers that a unit can undergo an online cleaning task after a minimum time period has passed from the occurrence of the previous online cleaning task in the same unit, as given by:

$$\begin{aligned} \sum_{t'=\max\{1, t-\gamma_i^{on}+1\}}^t V_{(i,t')} &\leq 1 & \forall i \in CB_i^{on}, t \in T \\ V_{(i,t)} &= 0 & \forall i \in CB_i^{on}, t \leq (\gamma_i^{on} - \tilde{\gamma}_i^{on}) : \tilde{\gamma}_i^{on} < \gamma_i^{on} \end{aligned} \quad (2-9)$$

Parameters  $\tilde{\gamma}_i^{on}$  and  $\gamma_i^{on}$  represent the total number of time periods that has passed since the last online cleaning at the beginning of the planning horizon and the minimum time between two consecutive online cleaning tasks in a unit, respectively.

$$V_{(i,t)} = \sum_{e \in E_i} V_{(e,i,t)}^{PR} \quad \forall i \in (CB_i^{on} \cap PR_i), t \in T \quad (2-10)$$

Constraints (2-10) relate the two binary variables for online cleaning tasks for the production units. These constraints are needed in order to model correctly the modified maximum operating levels of production units during the period that are under online cleaning. If online cleaning does not affect the maximum operating level of production units, then these constraints can be ignored and variables  $V_{(e,i,t)}^{PR}$  do not need to be defined.

#### 2.5.2.4 Condition-Based Cleaning Tasks: Unit Performance Degradation and Recovery

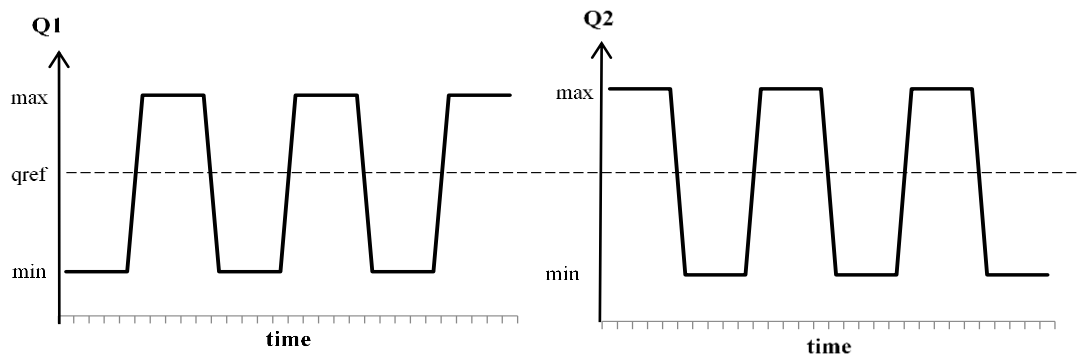
In this study, the performance of any unit that is subject to condition-based maintenance is modelled through the extra energy consumption of the unit  $U_{(i,t)}$  due to its deviation from its completely clean condition (i.e., full performance). The performance of the unit decreases as the extra energy consumption increases. To avoid the energy inefficient use and potential damage of the unit, this extra energy consumption for the units under operation should not exceed a maximum extra energy consumption limit  $v_i^{\max}$ , according to:

$$U_{(i,t)} \leq v_i^{\max} X_{(i,t)} \quad \forall i \in CB_i, \forall t \in T \quad (2-11)$$

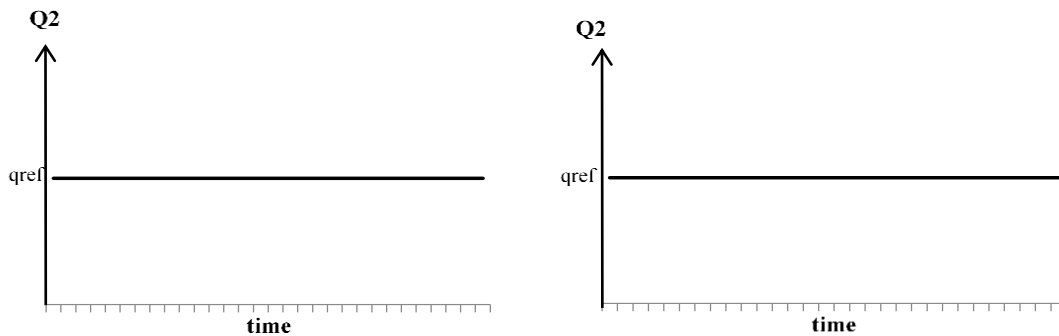
To continue with, the extra energy consumption of an operating unit is related to: (i) its cumulative time of operation  $R_{(i,t)}$ , and (ii) its cumulative operating level deviation  $D_{(i,t)}$  from its reference operating level (where additional energy consumption is considered minimal), as given by:

$$\begin{aligned}
U_{(i,t)} &\geq \delta_i R_{(i,t)} + \delta_i^{cd} D_{(i,t)} - v_i^{\max} (1 - X_{(i,t)}) & \forall i \in CB_i, \forall t \in T \\
U_{(i,t)} &\leq \delta_i R_{(i,t)} + \delta_i^{cd} D_{(i,t)} + v_i^{\max} (1 - X_{(i,t)}) & \forall i \in CB_i, \forall t \in T
\end{aligned}
\tag{2-12}$$

Parameters  $\delta_i$  and  $\delta_i^{cd}$  represent the degradation rates due to the cumulative time of operation and the deviation from the reference operating level, respectively. In industrial applications, it is significant to take into consideration the extra energy consumption contribution due to operation out of the reference operating level since this affects the condition of the equipment.



(a) Solution 1: units with different operating levels



(b) Solution 2: units with same operating levels.

**Figure 2-5 Illustrative example for operating level deviation of the units**

Figure 2-5 presents an illustrative example of two alternative operating level profiles of two units that produce the same product. Observe that the two solutions are equivalent in terms of total production level in any time period. On one hand, the first solution shows many operating level fluctuations and most importantly reports operating levels that are far away from the reference operating

level (i.e., this implies additional energy consumption). On the other hand, the second solution reports operating levels for both units equal to the reference operating level in all time periods (i.e., all  $D_{(i,t)}$  are zero). In other words, although the two solutions are equivalent in terms of total production, the smooth operation of the second solution results in reduced extra energy consumption and thus slower performance degradation of the unit.

#### 2.5.2.4.1 Cumulative time of operation

The occurrence of an offline cleaning task in a unit resets its cumulative time of operation to zero, according to:

$$R_{(i,t)} \leq \bar{\mu}_{(i,t)}(1 - W_{(i,t)}) \quad \forall i \in CB_i^{off}, \forall t \in T \quad (2-13)$$

Parameters  $\bar{\mu}_{(i,t)}$  are sufficiently large numbers. Good values for these parameters for each unit can be calculated through the corresponding maximum extra energy consumption and degradation rate parameters.

The cumulative time of operation for a unit subject to condition-based cleaning is modelled by the following set of constraints:

$$\begin{aligned} R_{(i,t)} &\leq (\tilde{\rho}_i + X_{(i,t)}) + \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, \forall t \in T : t = 1 \\ R_{(i,t)} &\leq (R_{(i,t-1)} + X_{(i,t)}) + \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, \forall t \in T : t > 1 \end{aligned} \quad (2-14)$$

$$\begin{aligned} R_{(i,t)} &\geq (\tilde{\rho}_i + X_{(i,t)}) - \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, \forall t \in T : t = 1 \\ R_{(i,t)} &\geq (R_{(i,t-1)} + X_{(i,t)}) - \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, \forall t \in T : t > 1 \end{aligned} \quad (2-15)$$

$$\begin{aligned} R_{(i,t)} &\geq (\tilde{\rho}_i + 1)(1 - \rho_i^{rec}) - \bar{\mu}_{(i,t)}(1 - V_{(i,t)}) & \forall i \in CB_i^{on}, \forall t \in T : t = 1 \\ R_{(i,t)} &\geq (R_{(i,t-1)} + 1)(1 - \rho_i^{rec}) - \bar{\mu}_{(i,t)}(1 - V_{(i,t)}) & \forall i \in CB_i^{on}, \forall t \in T : t > 1 \end{aligned} \quad (2-16)$$

For every unit, parameter  $\rho_i^{rec}$  represents the corresponding performance recovery factor due to its online cleaning and parameter  $\tilde{\rho}_i$  denotes the cumulative time of operation just before the beginning of the planning horizon of interest (i.e., initial state). Notice that a unit could be subject to both offline and online condition-based cleaning tasks in the proposed approach.

### 2.5.2.4.2 Cumulative operating level deviation

Similarly to the cumulative time of operation, the occurrence of an offline cleaning task in a unit resets its cumulative operating level deviation to zero, according to:

$$D_{(i,t)} \leq \mu_{(i,t)}(1 - W_{(i,t)}) \quad \forall i \in CB_i^{off}, \forall t \in T \quad (2-17)$$

Parameters  $\mu_{(i,t)}$  are sufficiently large numbers that could be calculated through the corresponding maximum extra energy consumption and degradation rate parameters.

For a utility unit subject to condition-based cleaning, the cumulative operating level deviation from its reference operating level ( $q_{(i,t)}^{ref}$ ) is modelled by the following set of constraints:

$$D_{(i,t)} \leq \tilde{\rho}_i^{cd} + \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) + \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) + \mu_{(i,t)}(1 - X_{(i,t)}) \quad \forall i \in (CB_i \cap UT_i), t \in T : t = 1 \quad (2-18)$$

$$D_{(i,t)} \leq D_{(i,t-1)} + \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) + \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) + \mu_{(i,t)}(1 - X_{(i,t)}) \quad \forall i \in (CB_i \cap UT_i), t \in T : t > 1$$

$$D_{(i,t)} \geq \tilde{\rho}_i^{cd} + \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) - \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) - \mu_{(i,t)}(1 - X_{(i,t)}) \quad \forall i \in (CB_i \cap UT_i), t \in T : t = 1 \quad (2-19)$$

$$D_{(i,t)} \geq D_{(i,t-1)} + \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) - \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) - \mu_{(i,t)}(1 - X_{(i,t)}) \quad \forall i \in (CB_i \cap UT_i), t \in T : t > 1$$

$$D_{(i,t)} \geq \left( \tilde{\rho}_i^{cd} + \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) \right) (1 - \rho_i^{rec}) - \mu_{(i,t)}(1 - V_{(i,t)}) \quad \forall i \in (CB_i^{on} \cap UT_i), t \in T : t = 1 \quad (2-20)$$

$$D_{(i,t)} \geq \left( D_{(i,t-1)} + \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) \right) (1 - \rho_i^{rec}) - \mu_{(i,t)}(1 - V_{(i,t)}) \quad \forall i \in (CB_i^{on} \cap UT_i), t \in T : t > 1$$

In this case, it is assumed that the reference operating level ( $q_{(i,t)}^{ref}$ ) is equal to the maximum operating level ( $K_{(i,t)}^{max}$ ) in order to avoid non-linear expressions of the model. The cumulative operating level deviation  $D_{(i,t)}$  becomes zero when the unit is in idle mode (i.e, not operating). This model is modified in Chapter 4 in which the cumulative operating level deviation becomes zero only if the unit undergoes an offline cleaning tasks.

For a production unit subject to condition-based cleaning, the cumulative operating level deviation from its reference production level ( $q_{(e,i,t)}^{ref}$ ) is modelled by the following set of constraints:

$$D_{(i,t)} \leq \tilde{\rho}_i^{cd} + \left( \frac{|q_{(e,i,t)}^{ref} - QE_{(e,i,t)}|}{q_{(e,i,t)}^{ref}} \right) + \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) + \mu_{(i,t)}(1 - X_{(i,t)})$$

$$\forall i \in (CB_i \cap PR_i), e \in E_i, t \in T : t = 1 \quad (2-21)$$

$$D_{(i,t)} \leq D_{(i,t-1)} + \left( \frac{|q_{(e,i,t)}^{ref} - QE_{(e,i,t)}|}{q_{(e,i,t)}^{ref}} \right) + \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) + \mu_{(i,t)}(1 - X_{(i,t)})$$

$$\forall i \in (CB_i \cap PR_i), e \in E_i, t \in T : t > 1$$

$$D_{(i,t)} \geq \tilde{\rho}_i^{cd} + \left( \frac{|q_{(e,i,t)}^{ref} - QE_{(e,i,t)}|}{q_{(e,i,t)}^{ref}} \right) - \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) - \mu_{(i,t)}(1 - X_{(i,t)})$$

$$\forall i \in (CB_i \cap PR_i), e \in E_i, t \in T : t = 1 \quad (2-22)$$

$$D_{(i,t)} \geq D_{(i,t-1)} + \left( \frac{|q_{(e,i,t)}^{ref} - QE_{(e,i,t)}|}{q_{(e,i,t)}^{ref}} \right) - \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) - \mu_{(i,t)}(1 - X_{(i,t)})$$

$$\forall i \in (CB_i \cap PR_i), e \in E_i, t \in T : t > 1$$

$$D_{(i,t)} \geq \tilde{\rho}_i^{cd} + \left( \frac{|q_{(e,i,t)}^{ref} - QE_{(e,i,t)}|}{q_{(e,i,t)}^{ref}} \right) (1 - \rho_i^{rec}) - \mu_{(i,t)}(1 - V_{(i,t)})$$

$$\forall i \in (CB_i^{on} \cap PR_i), e \in E_i, t \in T : t = 1 \quad (2-23)$$

$$D_{(i,t)} \geq D_{(i,t-1)} + \left( \frac{|q_{(e,i,t)}^{ref} - QE_{(e,i,t)}|}{q_{(e,i,t)}^{ref}} \right) (1 - \rho_i^{rec}) - \mu_{(i,t)}(1 - V_{(i,t)})$$

$$\forall i \in (CB_i^{on} \cap PR_i), e \in E_i, t \in T : t > 1$$

For every unit, parameter  $\tilde{\rho}_i^{cd}$  represents its cumulative operating level deviation just before the beginning of the planning horizon of interest (i.e., initial state).

### 2.5.2.5 Operational Constraints for Offline Cleaning Tasks

The following set of constraints ensure that a unit that is under offline cleaning remains closed for the whole duration of the selected offline cleaning task option, and relate the two binary variables for offline cleaning tasks.

$$X_{(i,t)} + \sum_{t'=\max\{\tau_i^{es}, t-v_{(i,q)}+1\}}^{\min\{\tau_i^{ls}, t\}} H_{(i,q,t')} \leq 1 \quad \forall i \in (FM_i \cup CB_i^{off}), q \in Q_i, \tau_i^{es} \leq t \leq (\tau_i^{ls} + v_{(i,q)} - 1) \quad (2-24)$$

$$W_{(i,t)} = \sum_{q \in Q_i} H_{(i,q,t)} \quad \forall i \in (FM_i \cup CB_i^{off}), t \in T : \tau_i^{es} \leq t \leq \tau_i^{ls} \quad (2-25)$$

For condition-based offline cleaning tasks, earliest and latest starting times should be set equal to the first and the last period of the planning horizon, respectively.

### 2.5.2.6 Resource Constraints for Cleaning Tasks

In the same line with the previous work in Chapter 2, a limited amount of available resources for cleaning operations shared by all types of cleaning tasks is considered, according to:

$$\sum_{i \in CB_i^{on}} \mathcal{G}_i^{on} V_{(i,t)} + \sum_{i \in CB_i^{off}} \sum_{q \in Q_i} \sum_{t'=\max\{\tau_i^{es}, t-v_{(i,q)}+1\}}^t \mathcal{G}_{(i,q)}^{off} H_{(i,q,t')} + \sum_{i \in FM_i} \sum_{q \in Q_i} \sum_{t'=\max\{\tau_i^{es}, t-v_{(i,q)}+1\}}^{\min\{\tau_i^{ls}, t\}} \mathcal{G}_{(i,q)}^{off} H_{(i,q,t')} \leq \eta_t^{\max} - \sum_{i \in DM_i} \tilde{\eta}_{(i,t)} \quad \forall t \in T \quad (2-26)$$

For every unit, parameters  $\mathcal{G}_i^{on}$  and  $\mathcal{G}_{(i,q)}^{off}$  denote the resource requirements for online cleaning and different offline cleaning task options, respectively.



## 2.5.3 Utility and Product Resources

### 2.5.3.1 Utility System: Operating Level Bounds

The utility system consists of a number of utility units that could generate the whole set of utility resources required by the production system. If a utility unit operates, its operating level should be between its lower and upper operating level bounds ( $\kappa_{(i,t)}^{\min}$  and  $\kappa_{(i,t)}^{\max}$ ). Here, changes in the maximum operating levels during online cleaning periods are considered and modelled through: (i) the binary variables related to online cleaning, and (ii) parameters  $\pi_i^{on}$  that represent the percentage modification on the upper operating level of a unit that is under online cleaning. Hence, the operating bounds of this general case are given by:

$$\kappa_{(i,t)}^{\min} X_{(i,t)} \leq QS_{(i,t)} \leq \kappa_{(i,t)}^{\max} (X_{(i,t)} - \pi_i^{on} V_{(i,t)}) \quad \forall i \in (UT_i \cap CB_i^{on}), t \in T \quad (2-27)$$

Notice that parameters  $\pi_i^{on}$  are activated only if there is an online cleaning task for a unit. In the case that there is no effect on the maximum operating level of some units during their online cleaning, the corresponding parameters  $\pi_i^{on}$  of these units are set equal to zero. There are some types of utility units, such as combined heat and power units, which generate at the same time more than one utility resources. The generated amount of any utility resource from each utility unit per time period is modelled by:

$$QE_{(e,i,t)} = \rho_{(e,i)}^{COGEN} QS_{(i,t)} \quad \forall i \in UT_i, e \in E_i, t \in T \quad (2-28)$$

Parameters  $\rho_{(e,i)}^{COGEN}$  denote the stoichiometry coefficients that relate the operating level of the utility unit with the generated amount of each utility resource type ( $QE_{(e,i,t)}$ ) that is cogenerated by the same utility system (e.g., heat to power ratio of a combined heat and power unit).

### 2.5.3.2 Production System: Production Level Bounds

The production system consists of a number of production units that produce the whole set of product resources required by the customers. Here, the production

process is modelled as single-stage with a number of units operating in parallel. In order to model the production statuses and levels for production units, the following binary variables are introduced:

$$Y_{(e,i,t)} = \begin{cases} 1 & \text{if production unit } i \in PR_i \text{ produces product resource } e \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

If a production unit produces a product resource  $e$ , its production level should be between its lower and upper production level bounds ( $\bar{K}_{(e,i,t)}^{\max}$  and  $\bar{K}_{(e,i,t)}^{\min}$ ). Similarly to utility units, changes in the maximum production levels during online cleaning periods are considered. Therefore, the production bounds of this general case are given by:

$$\bar{K}_{(e,i,t)}^{\min} Y_{(e,i,t)} \leq QE_{(e,i,t)} \leq \bar{K}_{(e,i,t)}^{\max} (Y_{(e,i,t)} - \pi_i^{on} V_{(e,i,t)}^{PR}) \quad \forall i \in (PR_i \cap CB_i^{on}), e \in E_i, t \in T \quad (2-29)$$

Online cleaning, as its name implies, could take place in time periods where production units are on operation, as modelled by:

$$V_{(e,i,t)}^{PR} \leq Y_{(e,i,t)} \quad \forall i \in (PR_i \cap CB_i^{on}), e \in E_i, t \in T \quad (2-30)$$

The two types of operating binary variables for the production units are related by the following set of constraints:

$$\begin{aligned} Y_{(e,i,t)} &\leq X_{(i,t)} & \forall i \in PR_i, e \in E_i, t \in T \\ X_{(i,t)} &\leq \sum_{e \in E_i} Y_{(e,i,t)} \leq 1 & \forall i \in PR_i, \forall t \in T \end{aligned} \quad (2-31)$$

According to these constraints, operating binary variables  $X_{(i,t)}$  would be equal to one if and only if there is production of a product resource. In addition, the latter constraints ensure that a production unit could produce at most one product resource per time period.

### 2.5.3.3 Inventory Tanks

Production and utility systems contain a number of resource-dedicated inventory tanks. These inventory tanks can receive resources ( $B_{(e,i,t)}^+$ ) from their associated units  $ZI_i^+$ , according to:

$$B_{(e,i,t)}^+ = \sum_{i \in (IT_e^+ \cap ZI_i^+)} QE_{(e,i,t)} \quad \forall e \in E, i \in IT_e, t \in T \quad (2-32)$$

Lower and upper bounds on the inlet flows of resources to inventory tanks are considered by:

$$\varepsilon_{(e,i,t)}^{+,min} \leq B_{(e,i,t)}^+ \leq \varepsilon_{(e,i,t)}^{+,max} \quad \forall e \in E, i \in IT_e, t \in T \quad (2-33)$$

Resource balances for every resource-dedicated inventory tank per time period are given by:

$$\begin{aligned} B_{(e,i,t)} &= \tilde{\beta}_{(e,i)} + B_{(e,i,t)}^+ - B_{(e,i,t)}^- & \forall e \in E, i \in IT_e, t \in T : t = 1 \\ B_{(e,i,t)} &= (1 - \beta_i^{loss}) B_{(e,i,t-1)} + B_{(e,i,t)}^+ - B_{(e,i,t)}^- & \forall e \in E, i \in IT_e, t \in T : t > 1 \end{aligned} \quad (2-34)$$

Notice that variables  $B_{(e,i,t)}$  indicate the inventory level per resource and inventory tank at the end of each time period and variables  $B_{(e,i,t)}^-$  represent the outlet resource flow from each inventory tank. Parameters  $\tilde{\beta}_{(e,i)}$  stand for the initial inventory for each resource inventory tank at the beginning of the planning horizon (i.e., initial state) and parameters  $\beta_i^{loss}$  provide the losses coefficients for each resource inventory tank. Minimum and maximum inventory levels for the inventory tanks are also considered as:

$$\xi_{(e,i)}^{min} \leq B_{(e,i,t)} \leq \xi_{(e,i)}^{max} \quad \forall e \in E, i \in IT_e, t \in T \quad (2-35)$$

The amount of each utility resource that leaves its dedicated inventory tank and its minimum and outlet flows are given by the following set of constraints:

$$B_{(e,i,t)}^- = \sum_{i \in (PR_i^- \cap ZI_i^-)} B_{(e,i,t)}^{UT,-} \quad \forall e \in E^{UT}, i \in IT_e, t \in T \quad (2-36)$$

$$\varepsilon_{(e,i,t)}^{-,min} \leq B_{(e,i,t)}^- \leq \varepsilon_{(e,i,t)}^{-,max} \quad \forall e \in E^{UT}, i \in IT_e, t \in T \quad (2-37)$$

### 2.5.3.4 Demands for Product Resources

The demands for final products ( $\zeta_{(e,t)}$ ) should be satisfied for every time period, according to:

$$NS_{(e,t)}^{FP} + \sum_{i \in ZI_i^-} B_{(e,i,t)}^- = \zeta_{(e,t)} \quad \forall e \in E^{PR}, t \in T \quad (2-38)$$

Variables  $NS_{(e,t)}^{FP}$  denote the amount of the demand for each product resource ( $E^{PR}$ ) per time period that cannot be satisfied by the internal production system. These unsatisfied demands for product resources should be covered by acquiring product resources from external sources. Generally speaking, this is highly undesirable and for this reason a very high penalty or purchase cost is usually used in the optimisation goal. If product resources cannot be acquired from external sources, variables  $NS_{(e,t)}^{FP}$  present the lost sales of product resources.

### 2.5.3.5 Demands for Utility Resources (Link between Utility and Production Systems)

The requirements for utility resources give the linking constraints between utility and production systems. For each time period, the demands for utility resources per production unit  $I^{PR}$  consist of: (i) fixed utility resource requirements that depend on the operational status of the production unit; and (ii) variable utility resource requirements that depend on the production level of the production unit.

$$\sum_{e' \in (E^{PR} \cap E_i)} (\alpha_{(i,e,e')} QE_{(e',i,t)} + \bar{\alpha}_{(i,e,e')} Y_{(e',i,t)}) = NS_{(e,i,t)}^{UT} + \sum_{i' \in (I_e \cap ZI_i^-)} B_{(e,i',i,t)}^{UT,-} \quad \forall e \in E^{UT}, i \in I^{PR}, t \in T \quad (2-39)$$

Variables  $NS_{(e,i,t)}^{UT}$  represent the amount of unsatisfied demand for each utility resource per time period. Similarly to the unsatisfied demand for product resources, penalty or purchase costs for acquiring utility resources from external sources are typically introduced in the objective function of the optimisation problem.

### 2.5.4 Objective Function

The optimisation goal is to minimise the total cost of the production and the utility system. More specifically, the objective function includes: (i) startup and shutdown costs for units that are subject to startup and shutdown actions; (ii) variable and fixed operating costs for utility units; (iii) variable and fixed production costs for production units; (iv) penalty or purchase costs for acquiring product and

utility resources from external sources; (v) total extra energy consumption costs for utility and production units that are subject to performance degradation modelling; and (vi) total cleaning costs related to online and offline cleaning tasks of production and utility units that are subject to performance degradation. The optimisation goal is given by:

$$\begin{aligned}
 \min \quad & \left[ \underbrace{\sum_{t \in T} \sum_{i \in I^{SF}} (\phi_{(i,t)}^S S_{(i,t)} + \phi_{(i,t)}^F F_{(i,t)})}_{\text{startup and shutdown}} + \underbrace{\sum_{t \in T} \sum_{i \in I^{UT}} (\phi_{(i,t)}^{UT,op-var} QS_{(i,t)} + \phi_{(i,t)}^{UT,op-fix} X_{(i,t)})}_{\text{utility units}} \right. \\
 & + \underbrace{\sum_{t \in T} \sum_{i \in PR_i} \sum_{e \in E_i} (\phi_{(e,i,t)}^{PR,op-var} QE_{(e,i,t)} + \phi_{(e,i,t)}^{PR,op-fix} Y_{(e,i,t)})}_{\text{production units}} \\
 & + \underbrace{\sum_{t \in T} \sum_{e \in E^{PR}} \phi_{(e,t)}^{PR,ex} NS_{(e,t)} + \sum_{t \in T} \sum_{e \in E^{UT}} \sum_{i \in I_{PR}^e} \phi_{(e,i,t)}^{UT,ex} NS_{(e,i,t)}}_{\text{purchase cost}} \\
 & \left. + \underbrace{\sum_{t \in T} \sum_{i \in CB_i} \phi_{(i,t)}^{pw} U_{(i,t)}}_{\text{extra energy consumption}} + \underbrace{\sum_{t \in T} \left( \sum_{i \in CB_i^{on}} \phi_{(i,t)}^{on} V_{(i,t)} + \sum_{i \in (CB_i^{off} \cup FM_i)} \sum_{q \in Q_i} \phi_{(i,q,t)}^{off} H_{(i,q,t)} \right)}_{\text{online and offline cleaning}} \right] \quad (2-40)
 \end{aligned}$$

In the above expression, the small-letter symbols correspond to the associated cost coefficients of the corresponding optimisation variables. A detailed definition of them can be found in the Nomenclature.

### 2.5.5 Remarks on Rolling Horizon

Terminal constraints should be defined for some key optimisation variables when a rolling horizon approach is used. These constraints are applied for the last time period  $|T|$  of the considered prediction horizon and can be typically related to desired minimum resource inventory levels or unit performance levels, as modelled below:

$$\begin{aligned}
 B_{(e,i,t)} &\geq \lambda_{(e,i)}^B \xi_{(e,i)}^{\max} & \forall e \in E, i \in IT_e, t \in T : t = |T| \\
 U_{(i,t)} &\leq \lambda_i^U v_i^{\max} & \forall i \in CB_i, t \in T : t = |T|
 \end{aligned} \quad (2-41)$$

Parameters  $\lambda_{(e,i)}^B$  and  $\lambda_i^U$  represent are percentage coefficients used to determine the minimum inventory level for each resource and the maximum extra energy consumption level for each operating unit at the last period of each prediction horizon. In the same line, terminal constraints could be defined for other variables

if needed. Generally speaking, terminal constraints are defined as a mean of preserving the stability of the system over its long-term operational horizon. It is also usual to apply terminal constraint values even in deterministic optimisation approaches, in order to ensure a better state of the system at the end of the planning horizon. More details about rolling horizon approaches can be found in Kopanos and Pistikopoulos (2014).

## **2.6 Case Studies**

In this part, three case studies for the integrated planning problem of utility and production systems are presented in order to highlight the special features of the proposed optimisation framework. More specifically, the first case study studies only a flexible time-window cleaning policy for units while the second case study considers both flexible time-window and condition-based cleaning policies for production and utility units. The third case study deals with the reactive planning problem under a rolling horizon approach and considers condition-based cleaning policies for all units. All case studies have been solved following both the proposed integrated approach and the traditional sequential approach. Detailed comparisons between the solutions of both approaches have been made. All resulting optimisation problems have been written in GAMS 24.8 (Brooke, et al., 1998) and solved with the MIP solver CPLEX 12.7 (ILOG, 2017) in an Intel(R) core(TM) i7-6700CPU@ 3.4 GHz with 8 GB RAM under standard configurations. A zero optimality gap has been imposed for all case studies.

### **2.6.1 Case Study 1: Integrated Planning of Utility and Production Systems (Flexible Time-Window Cleaning)**

In this case study, flexible time-window offline cleaning tasks for utility and production units are only considered (i.e., no condition-based maintenance). All parameters are deterministic. This optimisation problem requires about 100 seconds of CPU time to solve to zero optimality.

#### **2.6.1.1 Description of Case Study 1**

The system under consideration consists of five utility units ( $i1 - i5$ ) and three production units ( $i6 - i8$ ). The utility units can produce two utility resources ( $e1$ ,

$e2$ ) which could be either stored in their associated inventory tanks ( $z1, z2$ ) or consumed directly by the production units. Two final product resources ( $e3, e4$ ) can be produced by the production units that can be either stored in their dedicated inventory tanks ( $z3, z4$ ) or meet directly the customer demand. Each utility and production unit has a maximum operating level, as given by Table 2-1. Minimum operating levels for units are 10% of the corresponding maximum operating levels. For each production unit and product resource, Table 2-2 provides the stoichiometric coefficients of fixed and varied utility needs for the production of a unit of the associated product resource. Table 2-3 gives the cogeneration coefficient of each utility resource for every utility units. For example, for utility unit  $i1$ , four units of  $e2$  are generated for every unit of  $e1$  produced. Notice that utility unit  $i4$  and  $i5$  cannot generate utility resource  $e2$  and  $e1$ , respectively. Maximum runtimes for units are not considered. There is a maximum number of available resources for cleaning tasks equal to 12 cleaning resource units. The minimum runtime for utility and production units ( $\omega_i$ ) is 6 days and the minimum offline time after shutdown ( $\psi_i$ ) is 3 days. No lower bounds are considered for minimum inventory level ( $\xi_{(e,i)}^{\min}$ ), minimum flows of resources to inventory tanks ( $\varepsilon_{(e,i,t)}^{+, \min}$ ) and minimum flows of resources leaves inventory tanks ( $\varepsilon_{(e,i,t)}^{-, \min}$ ). There is no maximum resources flow constraint to inventory tank ( $\varepsilon_{(e,i,t)}^{+, \max}$ ). The maximum inventory level ( $\xi_{(e,i)}^{\max}$ ) for resources  $e1, e2, e3$ , and  $e4$  are 100, 320, 200 and 300 units, respectively. The maximum flows of utility resources leaving their respective inventory tank ( $\varepsilon_{(e,i,t)}^{-, \max}$ ) are 400 units for utility resource  $e1$  and 600 units for utility resource  $e2$ .

**Table 2-1 Case Study 1: Maximum operating levels for utility and production units**

$\kappa_{(e,i,t)}^{\max}$	<i>i1</i>	<i>i2</i>	<i>i3</i>	<i>i4</i>	<i>i5</i>	<i>i6</i>	<i>i7</i>	<i>i8</i>
<i>e1</i>	50	80	60	60	-	-	-	-
<i>e2</i>	200	160	180	-	140	-	-	-
<i>e3</i>	-	-	-	-	-	85	65	50
<i>e4</i>	-	-	-	-	-	65	50	85

**Table 2-2 Case Study 1: Fixed and varied stoichiometric coefficients of utility needs for production units (per unit of product resource)**

Unit	Product	$\alpha_{(i,e,e3)}$	$\alpha_{(i,e,e4)}$	$\bar{\alpha}_{(i,e,e3)}$	$\bar{\alpha}_{(i,e,e4)}$
<i>i6</i>	<i>e1</i>	0.90	0.80	17	15
	<i>e2</i>	2.25	3.38	45	39
<i>i7</i>	<i>e1</i>	0.80	0.70	14	18
	<i>e2</i>	3.38	5.25	54	30
<i>i8</i>	<i>e1</i>	0.75	0.90	16	10
	<i>e2</i>	2.63	3.00	36	48

**Table 2-3 Case Study 1: Cogeneration coefficients of utility units per utility resource**

$\rho_{(e,i)}^{COGEN}$	<i>e1</i>	<i>e2</i>
<i>i1</i>	1	4
<i>i2</i>	1	2
<i>i3</i>	1	3
<i>i4</i>	1	0
<i>i5</i>	0	1

A total planning horizon of 30 days, divided in day time periods (i.e., 30 time periods), is considered. All utility and production units should undergo a flexible time-window offline cleaning tasks. The earliest/latest cleaning startup times ( $\tau_i^{es} / \tau_i^{ls}$ ) are on day 9 and 15 for utility units and on day 20 and 25 for production units, respectively. There are three alternative flexible time-window offline cleaning options ( $q1, q2, q3$ ) that are characterised by different durations,



cleaning resources requirements and associated costs, as shown in Table 2-4. Operational costs for utility and production units are given in Table 2-5. Purchase costs for utility and product resources are 6,000 and 4,000 m.u./unit, respectively.

**Table 2-4 Case Study 1: Alternative options for flexible time-window offline cleaning tasks**

units	parameter	metric unit	$q1$	$q2$	$q3$
$i1 - i8$	$\nu_{(i,q)}$	days	3	4	5
$i1 - i8$	$\vartheta_{(i,q)}^{off}$	resource units	6	4	3
$i1, i2, i5 - i8$	$\phi_{(i,q,t)}^{off}$	m.u./cleaning	2,137.5	1,425.0	1,068.8
$i3$ and $i4$	$\phi_{(i,q,t)}^{off}$	m.u./cleaning	7,087.5	4,725.0	3,543.8

**Table 2-5 Case Study 1: Operational costs for utility and production units**

units	resource	$\phi_{(i,t)}^S$ (m.u./unit)	$\phi_{(i,t)}^F$ (m.u./unit)	$\phi_{(e,i,t)}^{op-fix}$ (m.u./unit)	$\phi_{(e,i,t)}^{op-var}$ (m.u./unit)
$i1$	$e1$ & $e2$	2,300	1,150	220	10
$i2$	$e1$ & $e2$	2,350	1,170	250	10
$i3$	$e1$ & $e2$	2,370	1,200	270	10
$i4$	$e1$	2,250	1,000	150	15
$i5$	$e2$	2,270	1,050	200	15
$i6$	$e3   e4$	2,300	1,150	500   400	1.2   1.0
$i7$	$e3   e4$	2,000	1,100	400   300	1.5   1.4
$i8$	$e3   e4$	2,300	1,150	300   500	1.4   1.9

The initial inventory for resources  $e1$ ,  $e2$ ,  $e3$  and  $e4$  is 10, 20, 50 and 300 units, respectively. It is assumed that the process plant is closed before the beginning of the planning horizon of interest, therefore there is no initial state (i.e.,  $\tilde{\chi}_i$ ,  $\tilde{\psi}_i$ , or  $\tilde{\omega}_i$ ) that is taken into account for this case study. In addition, Figure 2-6 shows the normalised demand for product resources by having the peak demand value of product resource  $e4$  as a reference. The range for demand for product

resource  $e3$  is between 40 to 100 units and for product resource  $e4$  is between 50 to 120 unit, respectively.

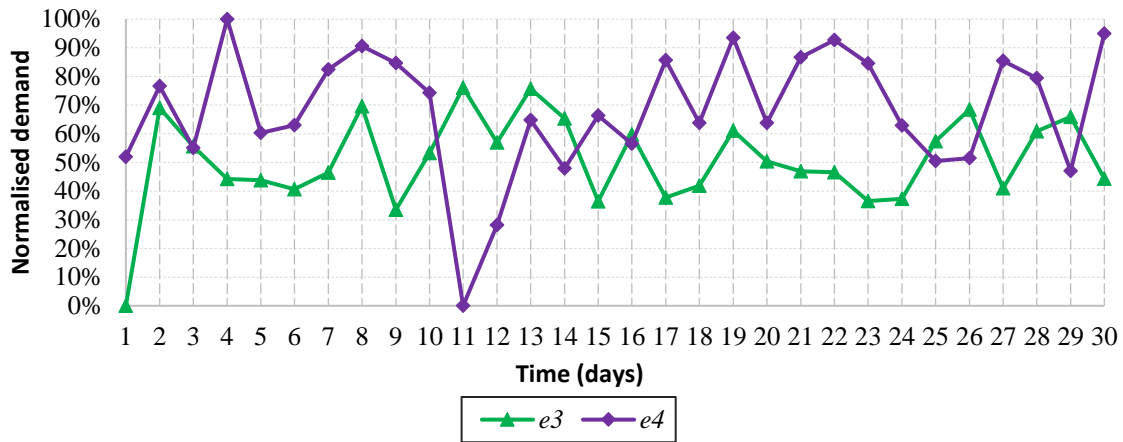


Figure 2-6 Case Study 1: Normalised demand profiles for products per time period

### 2.6.1.2 Results of Case Study 1 - Integrated Approach

This example has been solved by using the proposed integrated optimisation framework, and the results obtained are reported, analysed and discussed below.

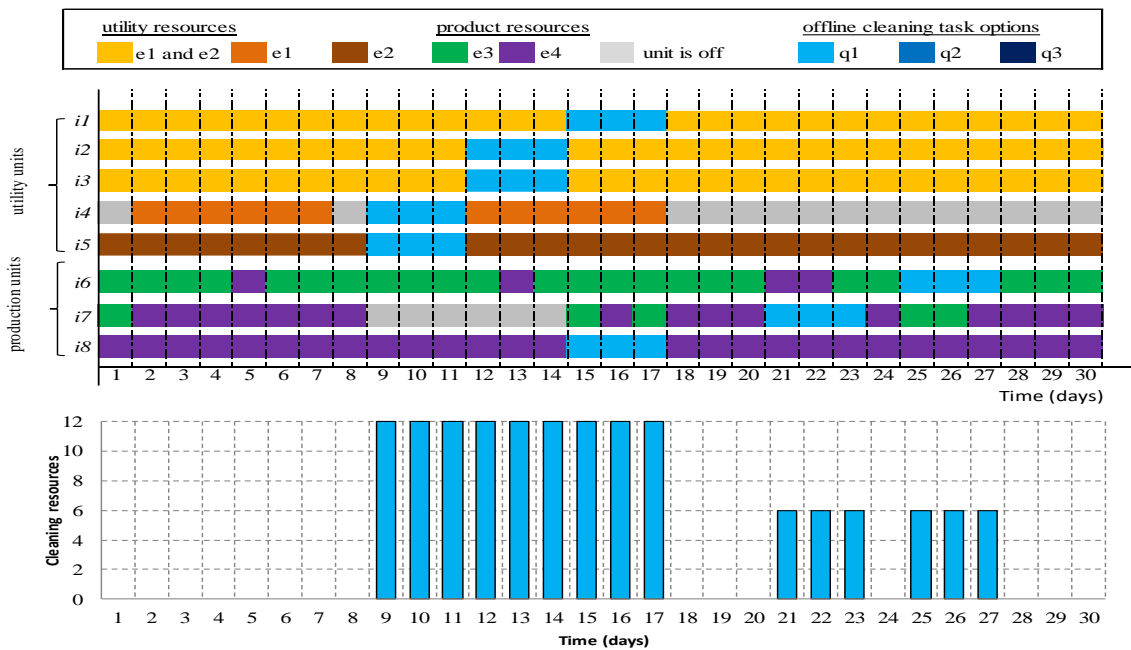
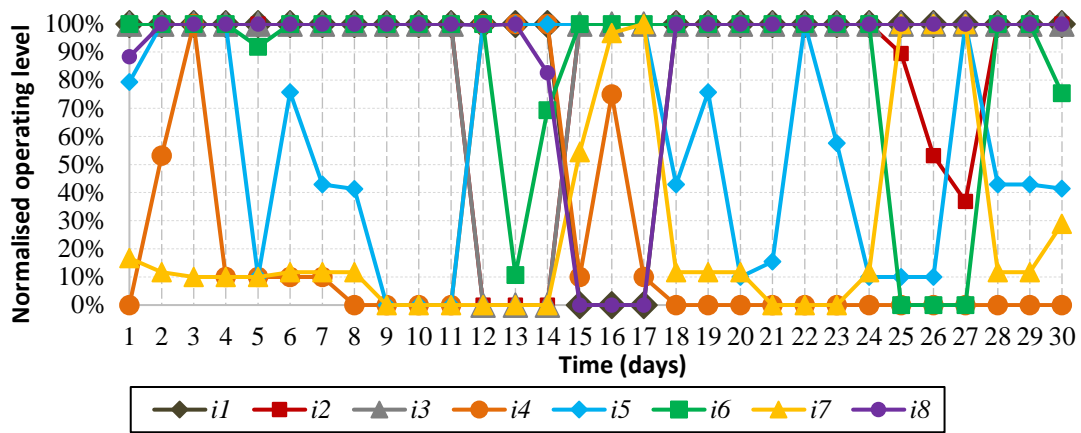


Figure 2-7 Case Study 1 - Integrated Approach: Optimal operational and cleaning plan for production and utility systems and total utilisation profile of cleaning resources

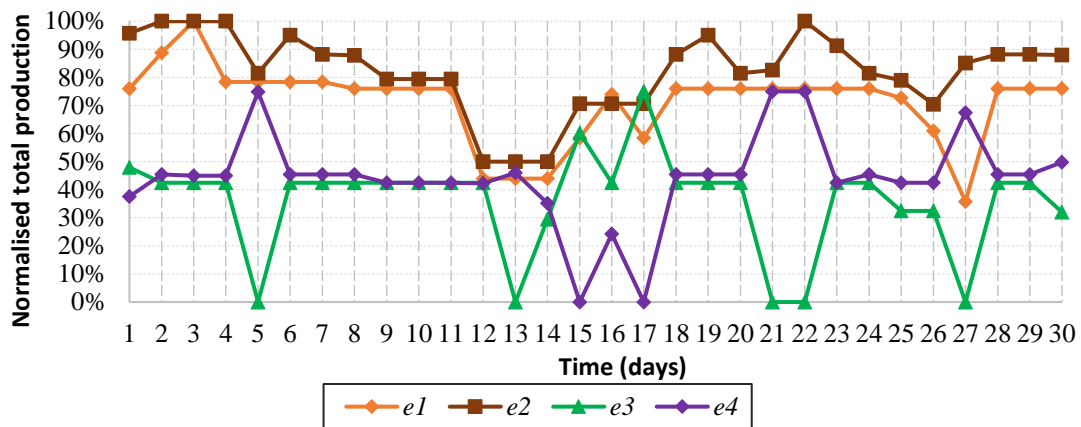
Figure 2-7 displays the optimal operational and cleaning plan for both the utility and the production system. More specifically, this figure shows for each unit per time period: (i) the operational status (i.e., in operation, idle, startup, shutdown, or under cleaning), (ii) the selected offline cleaning task options, (iii) the type of utility or product resources produced from each unit, and (iv) the profile of the cleaning resources requirements. No performance level profiles are displayed in this case study because no condition-based cleaning tasks are considered here.

Simultaneous cleaning tasks between utility units are observed. For instance, utility units  $i4$  and  $i5$  are under cleaning from day 9 to 11 and utility units  $i2$  and  $i3$  are under cleaning from day 12 to 14. In addition, it is observed a simultaneous cleaning for utility unit  $i1$  and production unit  $i8$  from day 15 to 17. The flexible time-window for the cleaning of production units is long enough to avoid simultaneous cleaning tasks of multiple production units. Notice that in the optimal solution the most expensive cleaning option  $q1$  (but with the smaller duration) has only been selected most probably because of: (i) the overall high demands for product resources throughout the planning horizon of interest; (ii) the relatively narrow flexible time-windows for the cleaning of utility units; (iii) the constrained availability of cleaning resources per time period; and (iv) the high purchase costs for utility and product resources. Utility unit  $i4$ , which can generate only utility resource  $e1$ , is not operating in day 1 and day 8, because there is enough supply of utility  $e1$  from the other utility units and its corresponding inventory tank. Production unit  $i7$  is idle from day 9 to 14 mainly due to following two reasons: (i) two utility units are under cleaning during these periods (see Figure 2-7) a fact that decreases the total utility generation capacity of the plant and therefore the total production capacity as well; and (ii) the total demands for products are relatively lower in these time periods (see Figure 2-6).



**Figure 2-8 Case Study 1 - Integrated Approach: Normalised operating level profiles for utility and production units**

Figure 2-8 displays the normalised operating level profiles for all utility and production units. The maximum operating level of each unit has been used as a reference of normalization (see Table 2-1). In the utility system, utility units *i1* to *i3* operate at their maximum operating levels throughout the planning horizon (excluding their cleaning periods). It is observed that utility unit *i4* that can generate only utility *e1* and utility unit *i5* that can generate only utility *e2* operate in a broader operating range to cover the fluctuations of the utility requirements of the production system. In the production system, production units *i6* and *i8* operate at their maximum capacities most of the time periods, while production unit *i7* operates at its minimum capacity. The latter is observed basically due to the relatively high shutdown costs compared to fixed and variable operating cost at the minimum operating level. For this reason, it is preferred to continue operating this production unit at minimum capacity and avoid shutting it down, since this would impose a considerable shutdown cost.

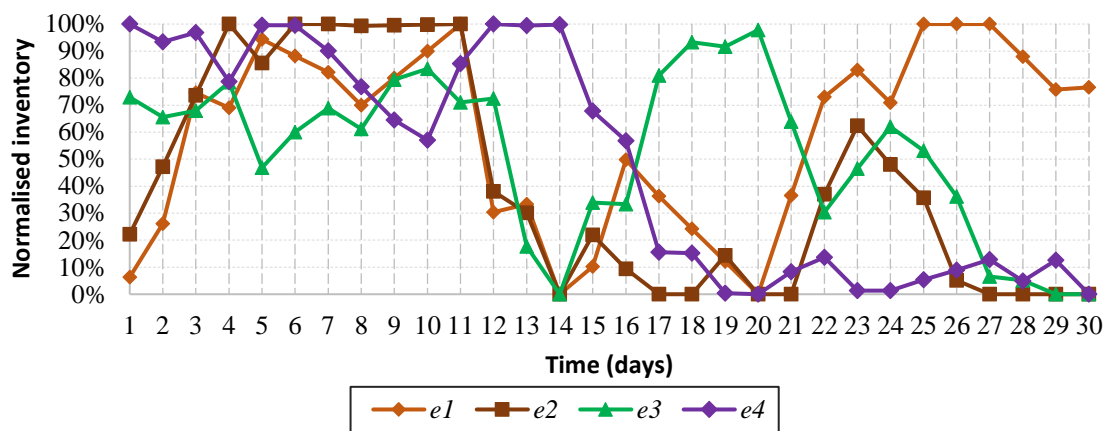


**Figure 2-9 Case Study 1 - Integrated Approach: Normalised total production profiles for utility and final product resources**

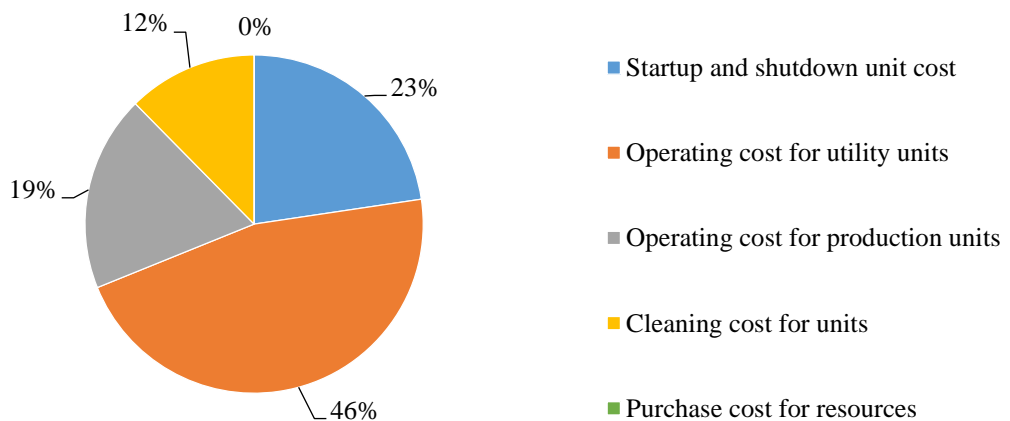
Figure 2-9 displays the normalised total production profiles for every utility and final product resource. The production of each resource is calculated by having the cumulative production of the resource from each unit divided by the maximum total resource capacity of all units. Not surprisingly, it is observed that the trend of the total production profile for  $e3$  follows the opposite trend of that of  $e4$ , since the limited number of production units can produce at most one final product per time period. For instance, the high total production peak levels for product resource  $e4$  instead of low total production levels for product  $e3$  in days 5, 13, 21, 22 and 27 are due to the fact that the production units produce exclusively product  $e4$  in all these days (see also Figure 2-7). The opposite trend is observed in day 15, and 17 when high total peak levels for product  $e3$  but low levels for product  $e4$  when production units produce only product  $e3$  in these days. Meanwhile, the production trends for utilities  $e1$  and  $e2$  follow quite a similar trend throughout the planning horizon, mainly due to the presence of three utility units that cogenerate both utility resources. For example, there is a reduction in the total operating levels for utility resources  $e1$  and  $e2$  when the utility units undergo cleaning between day 9 and 15.

Figure 2-10 displays the normalised inventory profiles for utility and product resources, having as reference the corresponding maximum inventory level of each inventory tank. Low utility inventory levels from day 12 to 20 are mainly due

to reduced utility capacities, because utility units  $i1$ ,  $i2$  and  $i3$  are under cleaning tasks in this period (see Figure 2-7). Importantly, there is no purchase of utility or product resources at any time period. From day 20 and onwards, the inventory levels of product resource  $e3$  are low because of: (i) the occurrence of a cleaning task in production unit  $i6$  (see Figure 2-7); and (ii) its high demands (as shown in Figure 2-6). Similarly, the low inventory profile for product  $e4$  from day 17 and onwards is due to its higher demand and the cleaning of production unit  $i7$  started in day 21.



**Figure 2-10 Case Study 1 - Integrated Approach: Normalised inventory profiles for utility and product resources**

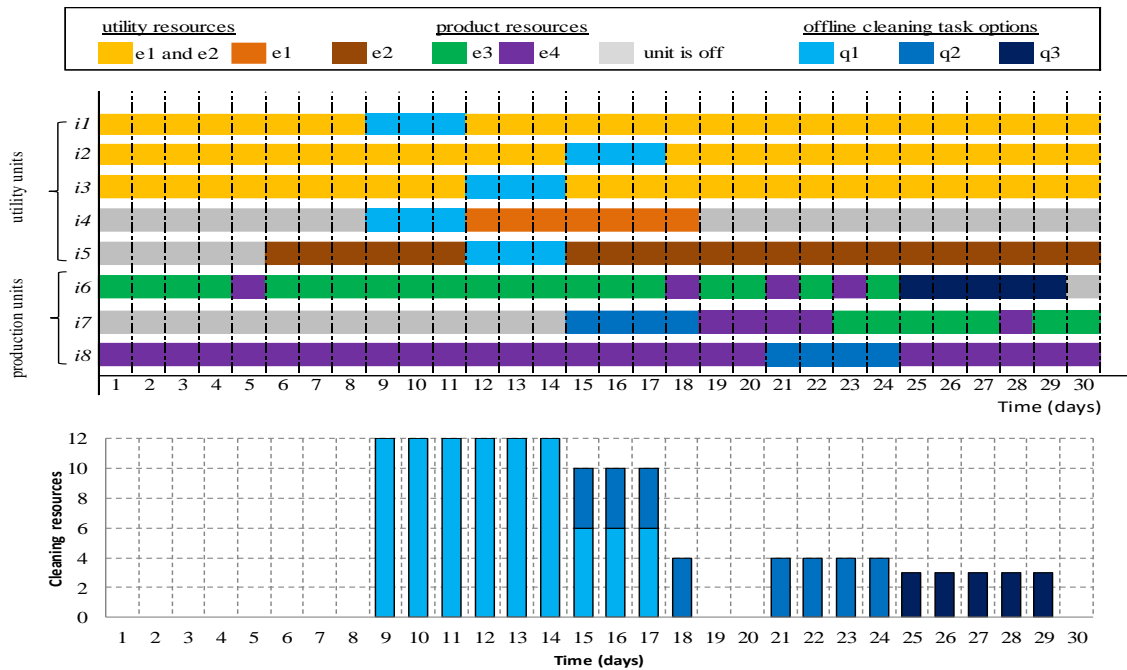


**Figure 2-11 Case study 1 - Integrated Approach: Total cost breakdown (percentage)**

Figure 2-11 shows the breakdown of the total cost for the utility and the production systems. The costs are divided into: (i) the startup and shutdown operations; (ii) the operation of the utility system; (iii) the operation of the production system; (iv) the offline cleaning tasks for the units; and (v) the total purchase of utility and product resources. The operational cost for the utility system remains the highest cost term at about 46% of the total cost. The second highest cost is the startup and shutdown units costs which is about 23% of the total cost, because of the initial state of the overall system (plant was closed before the beginning of the planning horizon). The cleaning cost is around 12% of the total cost while there is no purchase cost.

### 2.6.1.3 Results of Case Study 1 - Sequential Approach

In this section, the same case study has been solved considering the traditional sequential approach, where the planning problem of the production system is solved first using simply upper bounds on the total available utility amounts per time period. The right hand side of constraints (2-39) is replaced with the total utility generation. The model for the planning problem of the production system are constraints (2-1)–(2-7), (2-24)–(2,26), (2-31)–(2-35), and (2-38). After the solution of this production planning problem, the associated variables that describe the production of final products (i.e.,  $QE_{(e,i,t)}$  and  $Y_{(e,i,t)}$ ), product inventories and flows (i.e.,  $B_{(e,i,t)}$ ,  $B_{(e,i,t)}^-$ , and  $B_{(e,i,t)}^+$ ) and occurrence of cleaning tasks in the production units (i.e.,  $H_{(i,q,t)}$ ) are fixed, and the planning problem of the utility system is solved. The model for the planning problem of the utility system are constraints (2-1)–(2-7), (2-24)–(2-28), (2-32)–(2-37). This optimisation problem requires about 40 seconds of CPU time to solve to zero optimality.

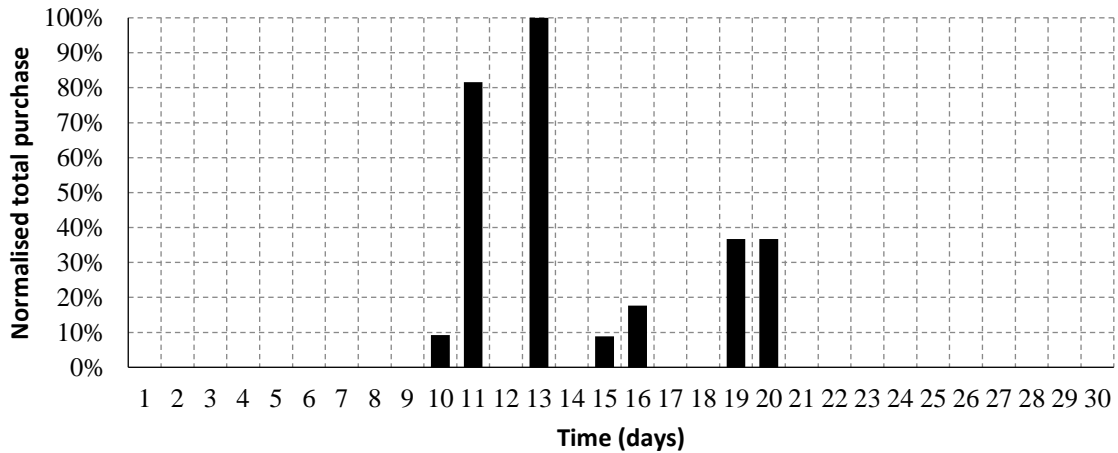


**Figure 2-12 Case Study 1 - Sequential Approach: Operational and cleaning plan for production and utility systems and total utilisation profile of cleaning resources**

Figure 2-12 displays the operational and cleaning plan for the production and the utility system obtained by following the sequential approach. In this case, cleaning tasks options  $q_2$  and  $q_3$  are selected for the production units. It should be emphasised, in contrast to the solution of the integrated approach, the solution of the sequential approach reports purchases of utilities from external sources in some time periods, as shown in Figure 2-13. In particular, important utility purchases are observed between day 10 and 16 because of the occurrence of multiple cleaning tasks in the utility units over this time window (see Figure 2-13). Furthermore, utility units  $i_4$  and  $i_5$  operate in less time periods in the solution of the sequential approach than in that of the integrated approach which cause the need for utility purchases (see Figure 2-7). A total of 633 units of utility resources need to be purchased throughout the planning horizon. If there is no option of acquiring utilities from external sources, this would make the production plan infeasible in practice. The total cost of the solution following the integrated approach is more than 5% lower than that of the solution found by the sequential



approach, which is a clear evidence of the benefits that the proposed integrated approach can have over its sequential counterpart.



**Figure 2-13 Case Study 1 - Sequential Approach: Normalised profile of total purchases for utilities**

### **2.6.2 Case Study 2: Integrated Planning of Utility and Production System (Condition-Based Cleaning and Flexible Time-Window Cleaning)**

In this case study, a condition-based cleaning policy for utility units and a flexible time-window cleaning policy for production units are considered. The condition-based cleaning policy involves online and offline cleaning tasks. All parameters are deterministic. This optimisation problem required about 18,000 CPU seconds to solve to zero optimality.

#### **2.6.2.1 Description of Case Study 2**

Here a modified version of the previous case study is considered. The main parameters (Table 2-1 to Table 2-4) and operational costs (Table 2-5) are the same as in Case Study 1. Minimum runtime and shutdown times are the same as in Case Study 1. The demand for products for this case study follows the same pattern as in the previous example, but reduced by 15%. A main difference here is that the utility units ( $i1-i5$ ) should undergo condition-based cleaning tasks. Meanwhile, production unit  $i6$  has a fixed offline cleaning and the other production units ( $i7-i8$ ) should undergo flexible time-window offline cleaning

tasks. The earliest and latest cleaning startup times ( $\tau_i^{es} / \tau_i^{ls}$ ) for production units  $i7$  and  $i8$  are in day 15 and 25, respectively. As before, there are three alternative cleaning tasks options that can be selected for condition-based offline cleaning (i.e., utility units) and time-window flexible cleaning (i.e., production units). The maximum available resources per time period for the cleaning tasks are 12 units of cleaning resources. The parameters that refer to condition-based offline and online cleaning for utility units are defined as follows: (i) the extra power consumption limit ( $v_i^{max}$ ); (ii) performance degradation rate ( $\delta_i$ ); (iii) performance coefficient related to operating level ( $\delta_i^{cd}$ ); (iv) minimum time between two consecutive online cleaning tasks ( $\gamma_i^{on}$ ); (v) the recovery factor of the online cleaning for any utility unit ( $\rho_i^{rec}$ ); (vi) references operating level ( $q_{(i,t)}^{ref}$ ); and (vii) the resource requirement of online cleaning ( $\vartheta_i^{on}$ ) as shown in Table 2-6.

**Table 2-6 Case Study 2: Parameters related to the condition-based cleaning of utility units**

Parameter	$i1$	$i2$	$i3$	$i4$	$i5$
$v_i^{max}$	162	153	247	200	210
$\delta_i$	9	9	13	10	10
$\delta_i^{cd}$	6.75	6.75	9.75	7.50	7.50
$\gamma_i^{on}$	10	10	10	10	10
$\rho_i^{rec}$	0.20	0.20	0.20	0.20	0.20
$q_{(i,t)}^{ref}$	50	80	60	60	70
$\vartheta_i^{on}$	1	1	1	1	1

At the end of the planning horizon of interest, there are two types of terminal constraints for the: (i) inventory levels of utility and product resources; and (ii) the performance level of the operating utility units. Namely, at the end of the planning horizon, the inventory levels of each resource should be greater or equal to 25%

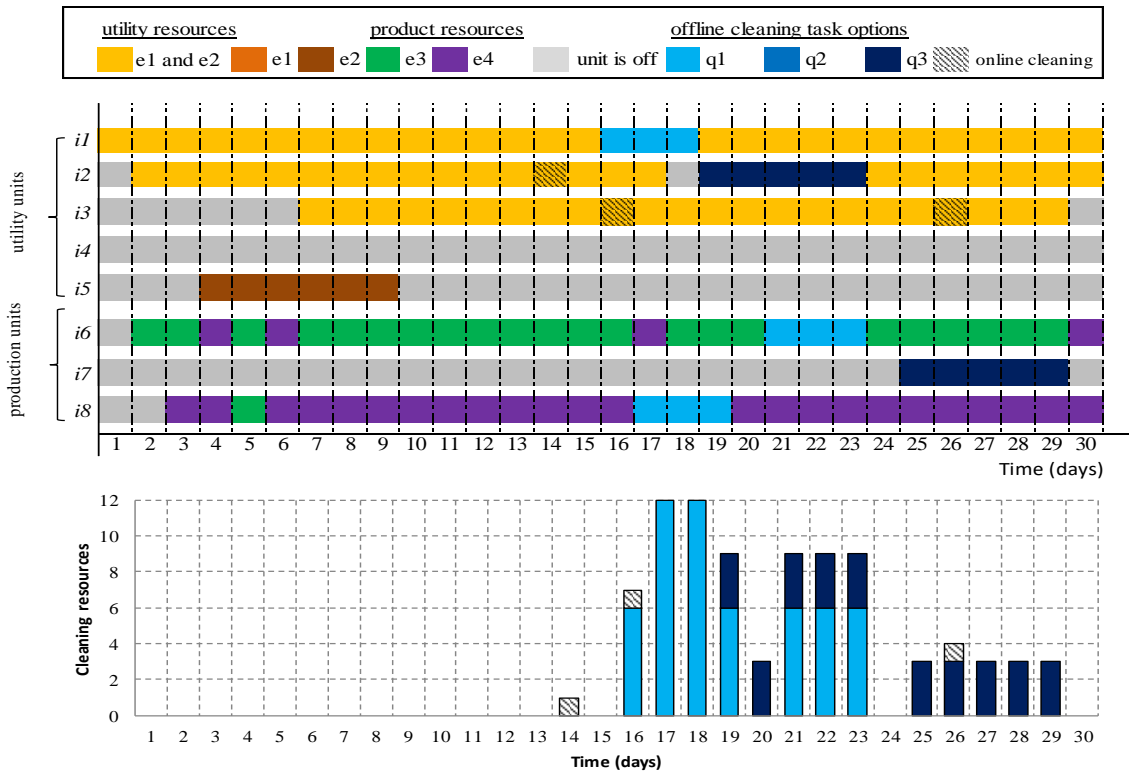
from its corresponding maximum inventory level ( $\zeta_{(e,i)}^{max}$ ), and the performance level of each utility unit that is under operation at the end of the planning should be greater or equal to 25% (i.e., lower or equal to 75% of the corresponding  $v_i^{max}$ ). In addition, Table 2-7 gives the values of the parameters that define the initial state of the utility and production systems. All other initial state parameters are zero.

**Table 2-7 Case Study 2: Initial state of the utility and production system**

Parameter	<i>i1</i>	<i>i2</i>	<i>i3</i>	<i>i5</i>
$\tilde{\rho}_i$	2	4	2	2
$\tilde{\beta}_{(e1,z1)}$	10	units	Initial inventory for utility <i>e1</i>	
$\tilde{\beta}_{(e2,z2)}$	20	units	Initial inventory for utility <i>e2</i>	
$\tilde{\beta}_{(e3,z3)}$	50	units	Initial inventory for product <i>e3</i>	
$\tilde{\beta}_{(e4,z4)}$	300	units	Initial inventory for product <i>e4</i>	

### 2.6.2.2 Results of Case Study 2 - Integrated Approach

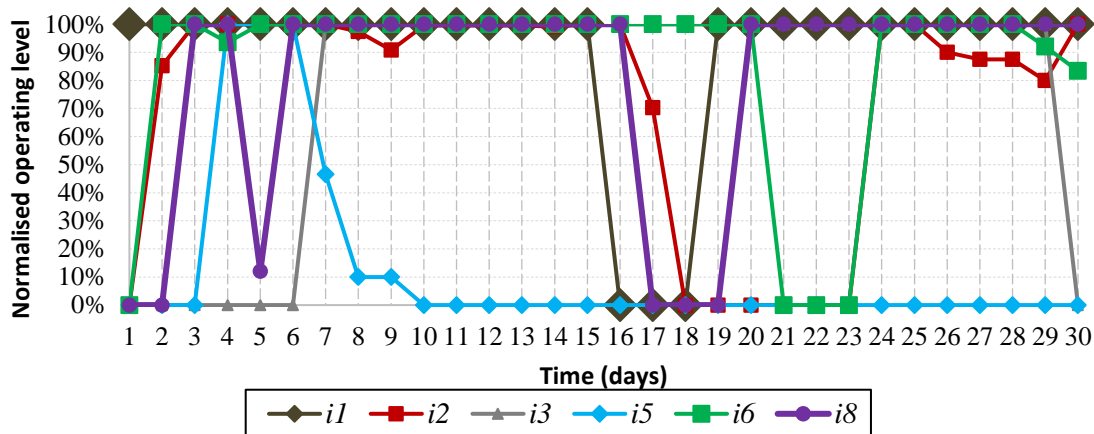
Figure 2-14 displays the optimal operational and cleaning plan for both production and utility system. For each production and utility unit: (i) the operational status at each time period; (ii) the selected offline cleaning tasks options and online cleaning tasks on its corresponding time period; (iii) the type of utility or product resources produced from each unit; and (iv) the profile of the cleaning resources requirements are observed.



**Figure 2-14 Case Study 2 - Integrated Approach: Optimal operational and cleaning plan for production and utility systems and total cleaning resources utilisation profile**

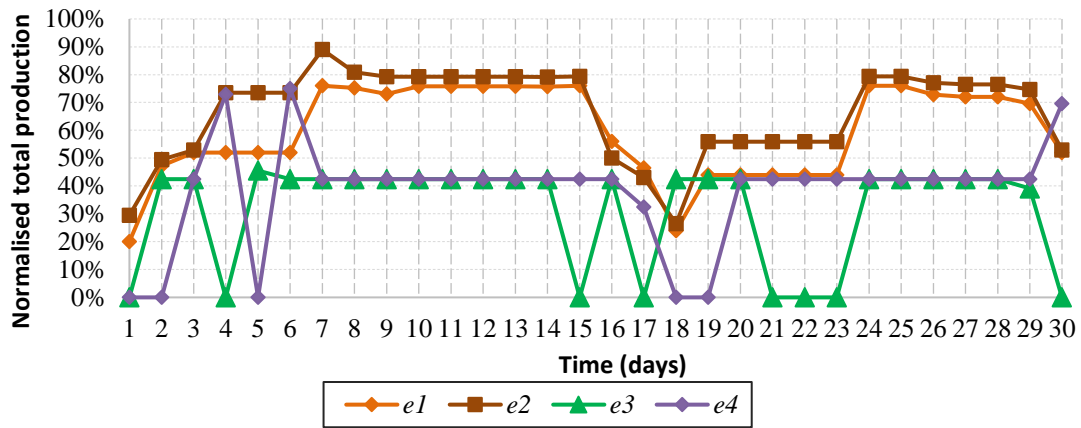
Simultaneous condition-based offline cleaning tasks are observed for utility unit  $i1$  and production unit  $i8$  in day 17 and 18. The solution reports condition-based cleaning tasks for utility units  $i1$  to  $i3$ . Meanwhile, utility unit  $i4$  that can only produce utility resource  $e1$  remains closed for all time periods because utility resource  $e1$  has enough supply from other utility units (e.g.,  $i1$ ,  $i2$  and  $i3$ ) that can cogenerate both utility resources. Utility unit  $i5$  which can only produce utility resource  $e2$  operates in a shorter duration from day 4 to 9 because utility unit  $i3$  is closed. The demand for utility resource  $e2$  cannot be satisfied by just utility unit  $i1$  and  $i2$ , thus utility unit  $i5$  operates to fully satisfy this demand in these days. Production unit  $i6$  produces product resource  $e3$  and production unit  $i8$  produces product resource  $e4$  in most of the time periods. This should be due to the stoichiometric coefficient  $\alpha_{(i,e,e')}$  and  $\bar{\alpha}_{(i,e,e')}$  that define the utility

requirements per product unit (see Table 2-2). Another observation is that, production unit  $i7$  remains idle throughout planning horizon but there is a predefined flexible cleaning task option  $q3$  that starts in day 25. It should clear here that the longest duration cleaning task option is selected due to its lower cost. In reality, the production manager may find that this cleaning is not necessary because this production unit does not operate in the current planning horizon, and may ignore it.



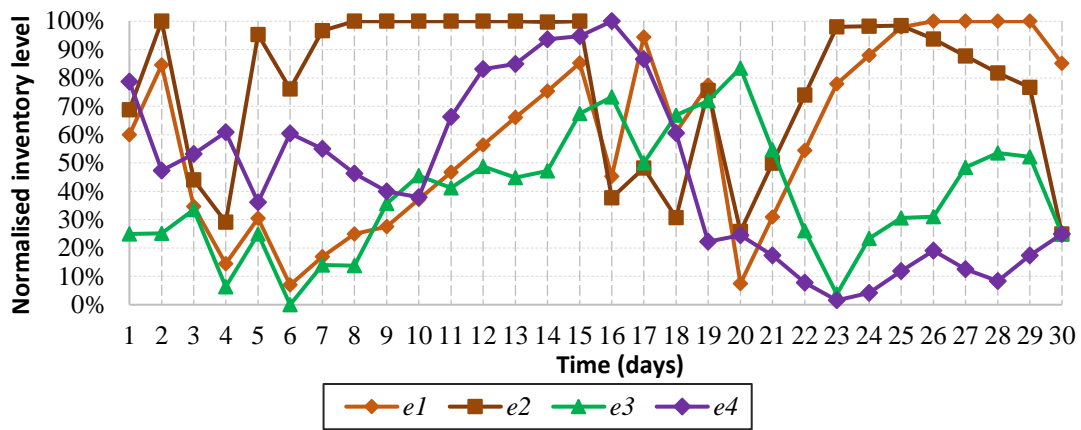
**Figure 2-15 Case Study 2 - Integrated Approach: Normalised operating level profiles for utility and production units**

Figure 2-15 displays the normalised operating level profiles for utility and production units, having as a reference the maximum operating level of each unit as given in Table 2-1. In the utility system, utility units  $i1$  to  $i3$  operate at their maximum operating levels throughout the planning horizon (excluding their cleaning periods). Utility unit  $i5$ , which can generate only utility resource  $e2$ , operates from day 4 to 9 to satisfy the needs for utility resource  $e2$ . Maximum production level for utility units  $i5$  is observed from day 4 to 6 because utility unit  $i3$  is offline (refer to Figure 2-14). Then, the production level for utility unit  $i5$  reduces to minimum because utility unit  $i3$  starts up in day 7. In the production system, production units  $i6$  and  $i8$  operate in their maximum capacity almost in all time periods in order to satisfy the high demand for product resources.



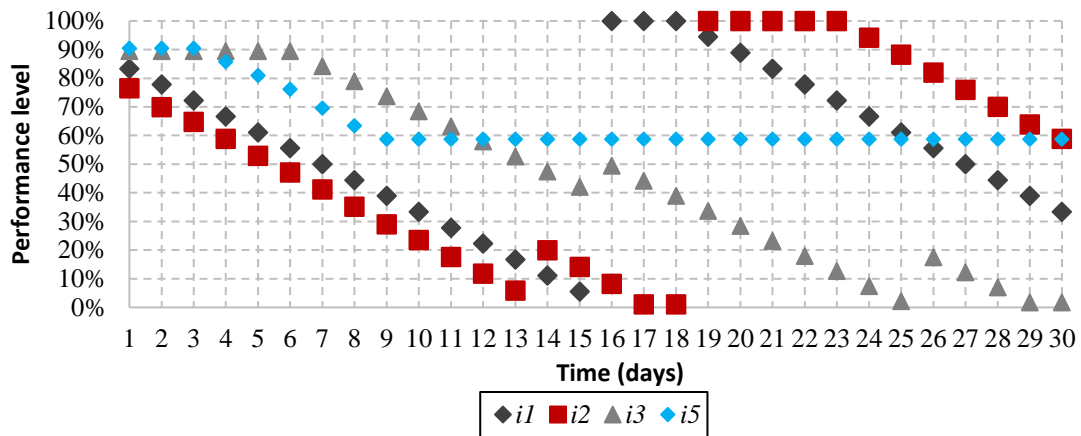
**Figure 2-16 Case Study 2 - Integrated Approach: Normalised total production profiles for utility and final product resources**

Figure 2-16 displays the normalised total production profiles for every utility and final product resource. The total production for each resource is calculated by having the cumulative production of the resource from each unit divided by the maximum total resource capacity from all units. The production trends for utility resources *e1* and *e2* follow quite a similar trend throughout the planning horizon, mainly due to the presence of three utility units that cogenerate both utility resources. The only differences are observed when utility unit *i5* operates from day 4 to 9. There are higher production differences for utility resource *e2* than that of the production of utility resource *e1*. The total production level for utility resources *e1* and *e2* are considerably reduced when cleaning takes place for utility units between days 16 and 23. The production profiles for product resources *e3* and *e4* from day 7 to 14 and from day 24 to 28 are on the same level because the upper operating level of utility unit *i6* (produces product resource *e3*) and utility unit *i8* (produces product resource *e4*) in all these days are the same (see Table 2-1). In addition, when there is no production of a product resource in certain time periods (e.g., days 1, 4, 15, 17, 21, 22, 23, 30 for product resource *e3* and days 1, 2, 5, 18, 19 for product resource *e4*) its corresponding demand is fully satisfied from its associated inventory tank.



**Figure 2-17 Case Study 2 - Integrated Approach: Normalised inventory profiles for utility and product resources**

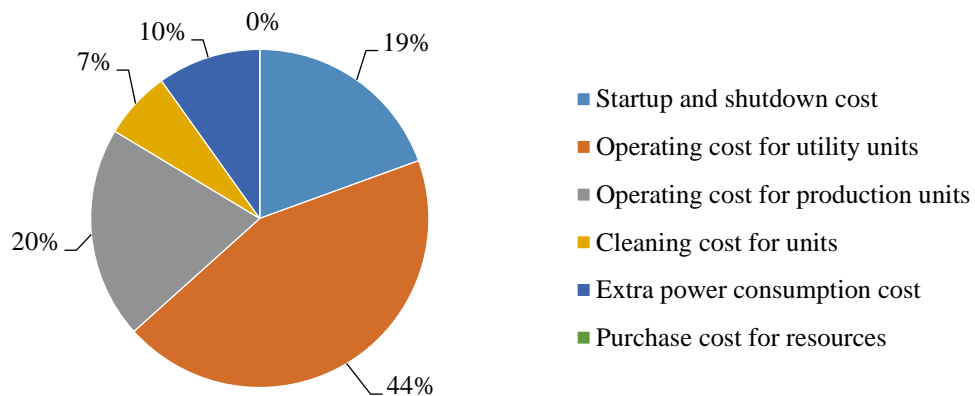
Figure 2-17 displays the normalised inventory profiles for utility and product resources. The maximum inventory levels ( $\xi_{(e,i)}^{max}$ ) are the reference values here. It is observed that, high inventory level for utility and product resources at the beginning of planning horizon because of initial inventory levels. There are reduced inventory levels for utility and product resources on day 16 to 23 because cleaning of utility unit  $i1$  and  $i2$  and production unit  $i6$  and  $i8$  take place on these days. At the end of day 30, the inventory level for utility  $e2$  and product  $e3$  and  $e4$  are not approaching zero due to terminal constraints are set to be 25% of the initial inventory. However, this is not the case for utility  $e1$  because all utility units (i.e.,  $i1, i2$  and  $i3$ ) that cogenerate both utilities are operating at their maximum operating capacities (refer to Figure 2-15). It is not possible to operate these utility units in a lower capacity at the end of the planning horizon because the utility demand for  $e2$  must be fully satisfied in order to meet the demand for products. Thus, the optimal solution reports a 25% of inventory level for utility  $e2$  and a much higher inventory level for utility  $e1$  at the end of planning horizon.



**Figure 2-18 Case Study 2 - Integrated Approach: Performance level profiles for utility units per time period**

Figure 2-18 shows the performance level profiles for utility units that are subject to condition-based cleaning. The performance level of a unit depends on its cumulative time of operation and its operating levels deviation. Here, it can be seen when the performance of utility units *i1* and *i2* is fully recovered once an offline cleaning occurs. It is also observed that utility unit *i2* partially recovers its performance through an online cleaning in day 14, and it continues operating until reaching its critical performance level in day 17. The performance degradation of utility unit *i5* declines in a slightly varied rate (i.e., no straight line decline) from day 7 to 9 due to the deviation of its operating level from its maximum operating capacity (see Figure 2-15). Utility unit *i5* shuts down in day 10 and remains idle for the remaining planning horizon, thus no cleaning task is performed after its shutdown. The performance levels of all operating utility units at the end of the planning horizon remain above 25% (due to the terminal constraints imposed) except for utility unit *i3* that does not operate in day 30 and therefore terminal constraint was not applied (see Figure 2-14). In practice, one could start an offline cleaning task on this unit at the last period of the planning horizon to completely restore its performance.



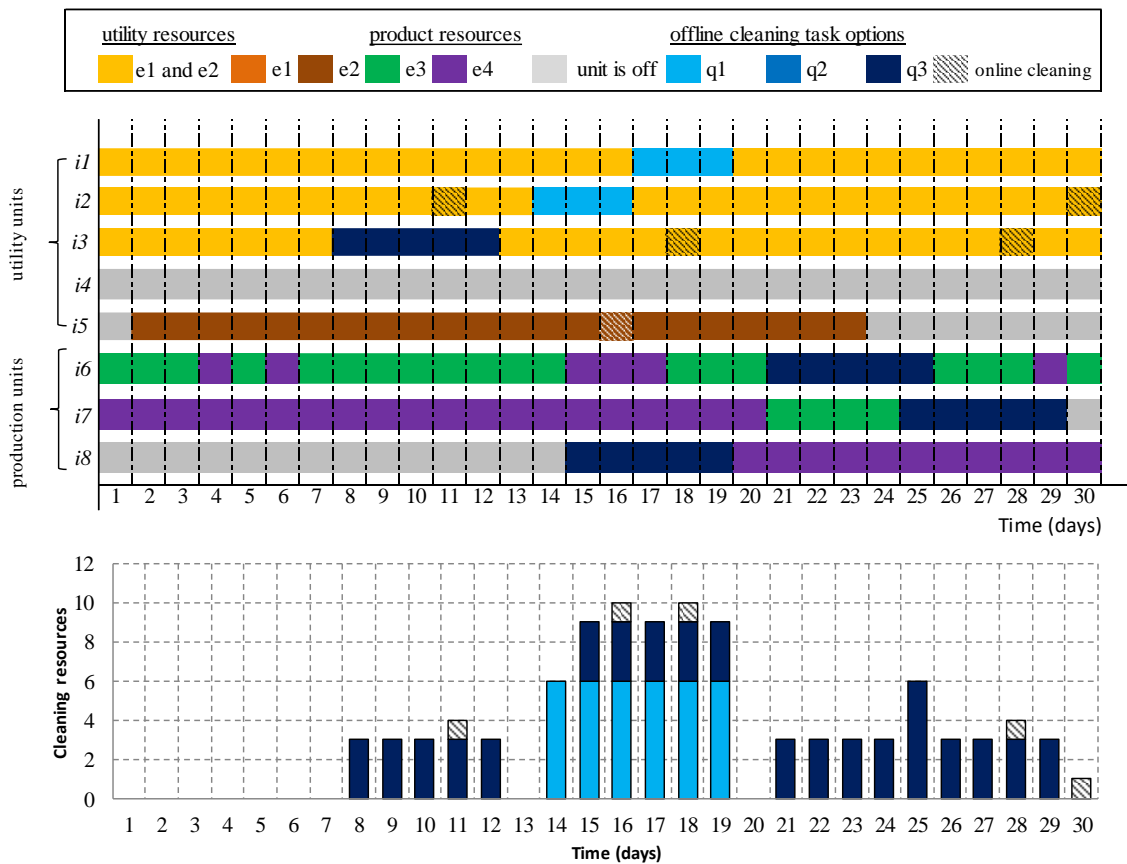


**Figure 2-19 Case Study 2 - Integrated Approach: Total cost breakdown (percentage)**

Figure 2-19 demonstrates the total cost breakdown for the utility and production systems. As in the previous case study, the operating cost of the utility system remains the highest cost term. This is because the production levels of utility resources to satisfy the utility demand of the production system are much higher than the production levels of the production system. Also, variable and fixed utility costs are relatively expensive. The startup and shutdown cost and the operating cost of the production system are at 19% and 20% of the total cost, respectively. The extra energy consumption and cleaning costs are around 10% and 7%.

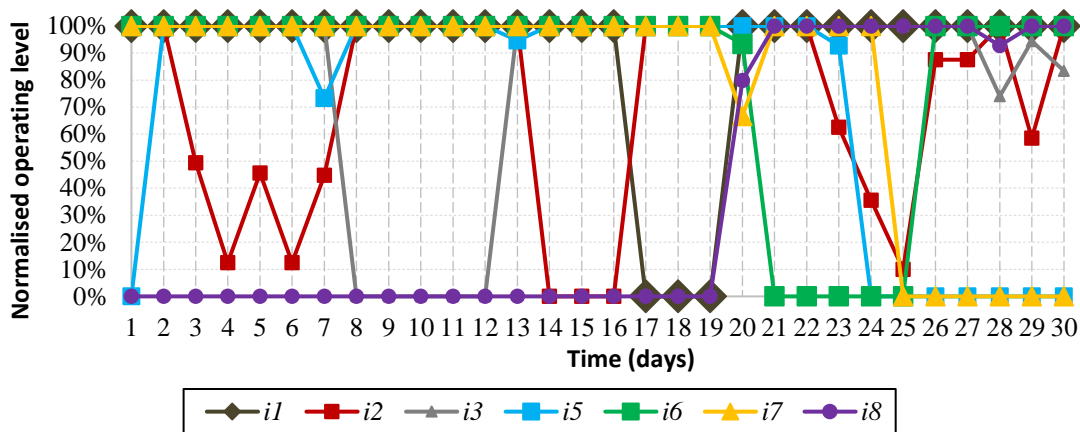
### 2.6.2.3 Results of Case Study 2 - Sequential Approach

The same case study has been solved following the traditional sequential approach in order to make a comparison of its solution with the solution obtained by the proposed integrated approach. This optimisation problem requires over 1,000 seconds of CPU time to solve to zero optimality.



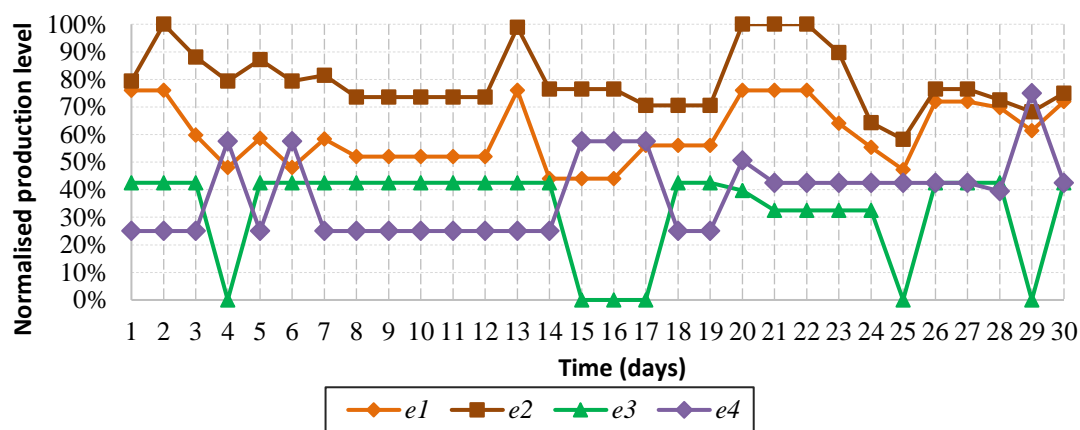
**Figure 2-20 Case Study 2 - Sequential Approach: Operational and cleaning plan for production and utility systems and total utilisation profile of cleaning resources**

Figure 2-20 displays the optimal operational and cleaning plan for the sequential approach. In comparison with the integrated approach, a higher number of online cleaning tasks for utility units are observed. Some major observations are that: (i) utility unit *i4* still remains inactive throughout the whole planning horizon; (ii) utility unit *i5* operates in a larger number of time periods than before; and (iii) production unit *i7* now operates in most of the time periods and production unit *i8* operates less time in the 30-day planning horizon.



**Figure 2-21 Case Study 2 - Sequential Approach: Normalised operating level profiles for utility and production units**

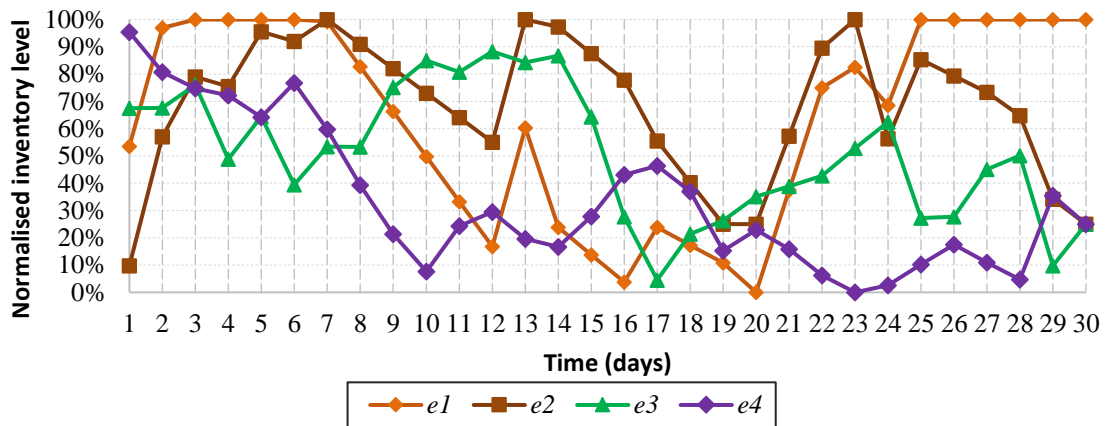
Figure 2-21 shows the normalised operating level profiles for utility and production units of the solution of the sequential approach. In comparison with the solution of the integrated approach (Figure 2-15), utility units *i1* and *i3* operate at their maximum operating levels while the operating level of utility unit *i2* varies in order to accommodate the demand for utility resources. Utilised production units operate on their maximum operating capacities most of the times.



**Figure 2-22 Case Study 2 - Sequential Approach: Normalised total production profiles for utility and product resources**

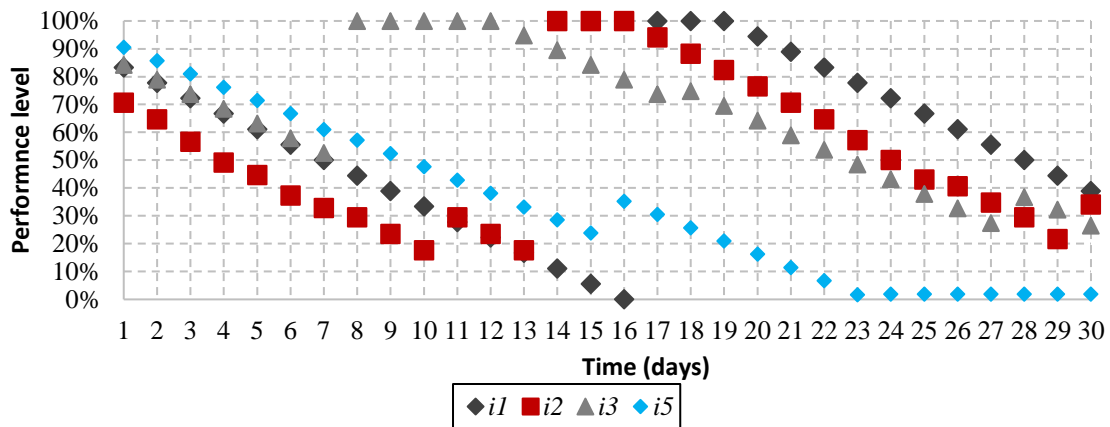
Figure 2-22 displays the normalised total production profiles for utility and product resources. The production profiles for utility resources *e1* and *e2* follow quite a

similar pattern throughout planning horizon. Since a production unit can produce at most one product resource per time period and there is a limited number of production units, the production profile for product resource  $e3$  follows the opposite trend of that of product resource  $e4$ .



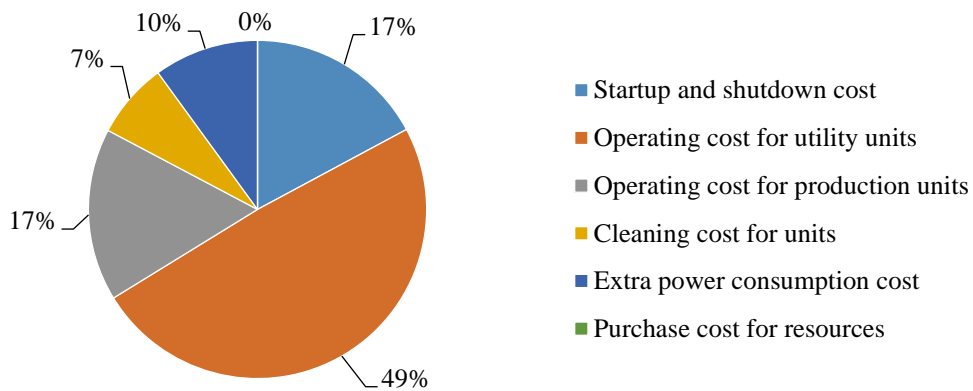
**Figure 2-23 Case Study 2 - Sequential Approach: Normalised inventory profiles for utility and product resources**

The normalised inventory profiles for utility and product resources are shown in Figure 2-23. The inventory levels for utility resources  $e1$  and  $e2$  are lower in day 14 to 19, which is due to the offline and online cleaning of the utility units (see Figure 2-20). The inventory level for product resource  $e3$  reduces considerably from day 15 and 17 because no production unit is producing product resource  $e3$  in these days and the corresponding demand is satisfied exclusively from its inventory tank. At the end of day 30, the inventory level for utility resource  $e2$  and product resources  $e3$  and  $e4$  are equal to 25% of their maximum inventory capacity due to the terminal constraints imposed. However, a much higher inventory level is for utility resource  $e1$  is reported, similarly to the solution of the integrate approach. As explained before, this is mainly due to the existence of utility cogeneration units that cogenerate both utilities under different generation ratios (see Table 2-3).



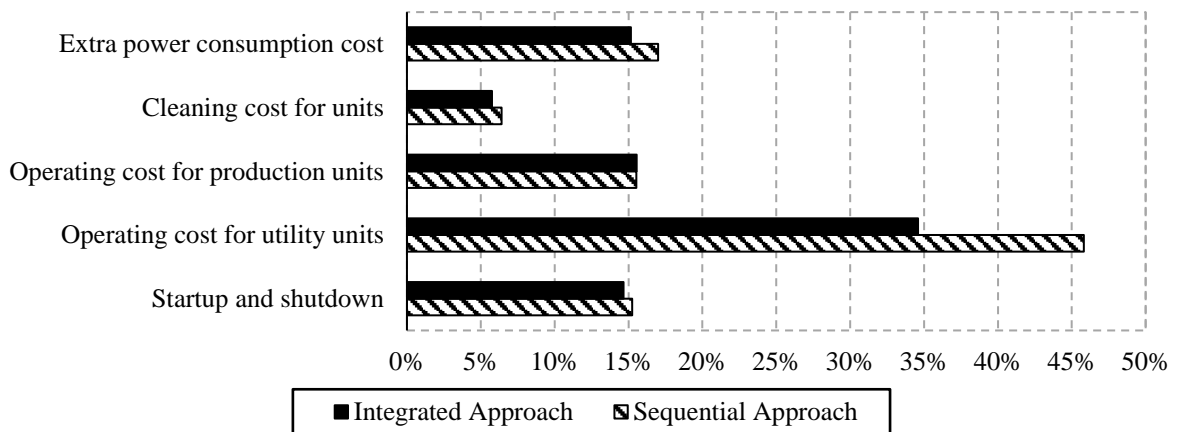
**Figure 2-24 Case Study 2 - Sequential Approach: Performance level profiles for utility units per time period**

The performance level profiles for active utility units are displayed in Figure 2-24. It can be seen that the performance level of utility unit *i2* decreases according to the variation in its operating levels. Utility units *i1*, *i2* and *i3* fully recover their performances by undergoing offline cleaning tasks, while utility unit *i5* undergoes online cleaning in day 16 to partially recover its performance. The performance levels of all operating utility units at the end of the planning horizon remain above 25% (due to the terminal constraints imposed) except for utility unit *i5* that does not operate in day 30 and therefore terminal constraint was not applied (see Figure 2-14). In practice, one could perform an offline cleaning on this unit after day 22 to completely restore its performance by the end of the planning horizon.



**Figure 2-25 Case Study 2 - Sequential Approach: Total cost breakdown (percentage)**

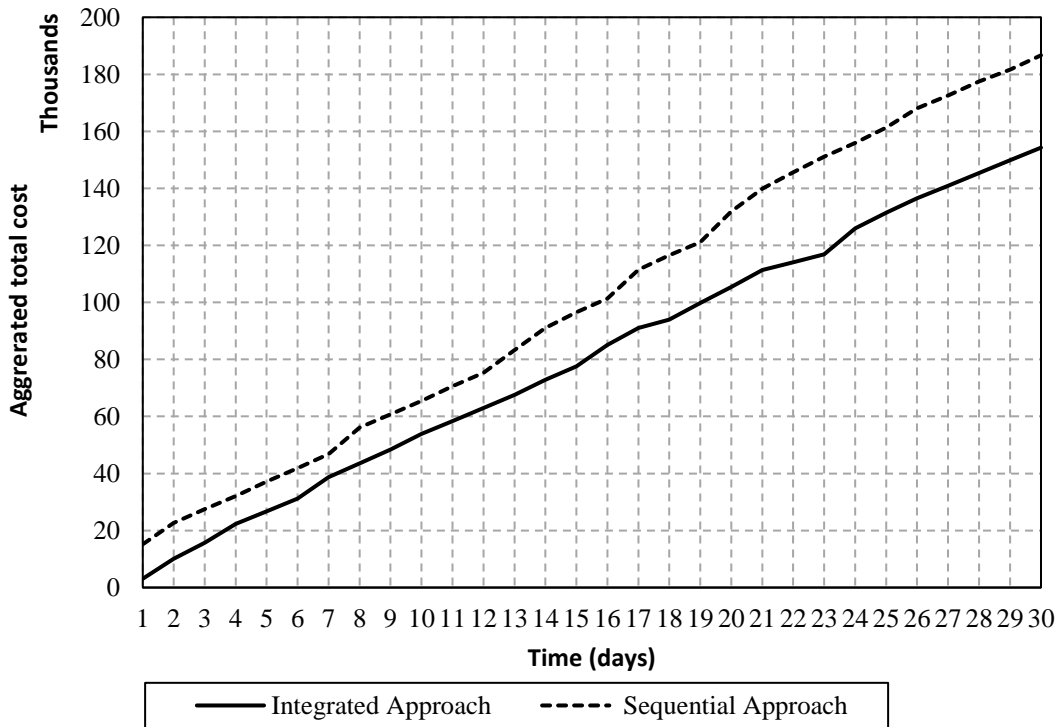
Figure 2-25 shows the total cost breakdown for the solution of the sequential approach. The operating cost for utility units is 49% which is 5% higher than the percentage of the operating cost of the integrated approach (refer to Figure 2-11). This is because utility unit *i5* operates for a longer horizon in sequential approach in comparison with the integrated approach.



**Figure 2-26 Case Study 2: Cost term comparison of integrated and sequential approach**

Figure 2-26 shows the cost comparison of the solutions derived by following the integrated and the sequential approach. Each cost term for both solutions is divided by the total cost for sequential approach (which is higher than that of the integrated approach). The major cost difference between the solution of the

integrated and the sequential approach is the operating cost for utility units is about 13%. This difference in the operating cost for utility system affect strongly the total cost of the solution found by the sequential approach. The extra energy consumption cost, cleaning cost and startup and shutdown cost show cost differences of around 1%. The operating cost for production units is almost the same for both approaches.



**Figure 2-27 Case Study 2: Aggregated total cost for integrated and sequential approach**

Figure 2-27 displays the evolution of the total cost value over time for both approaches. This difference significantly increases by the end of the planning horizon. The vertical difference between the two lines in the graph shows the difference of the total cost between the two solutions. In particular, it is observed that the total cost of the solution of the integrated approach is 17% lower than that of the sequential approach demonstrating clearly the benefits of the proposed integrated approach.

### 2.6.3 Case Study 3: Integrated Planning of Utility and Production Systems via Rolling Horizon Approach

In this example, the reactive integrated planning problem of utility and production systems through a rolling horizon approach is considered in order to show how the proposed optimisation framework can be readily used in a dynamic environment. For the rolling horizon approach, a prediction horizon equal to 15 time periods and a single-period control horizon have been used. A time period is equal to one day. The total planning horizon of interest is 30 days, therefore a total number of 30 iterations have been solved (30 optimisation problems). For each iteration, a planning problem for the next 15 time periods is solved with updated information of the current state of the overall system and the demand for product resources. Only the solution of the first time period of the current prediction horizon is applied at each iteration, and the initial state of the next iteration is updated accordingly. In this case study, all utility and production units are subject to alternative condition-based cleaning policies. This case study requires in average of 400 seconds of CPU time for each optimisation problem.

#### 2.6.3.1 Description of Case Study 3

This example is a slight modified version of the previous case study. The main parameters (Table 2-4) and operational costs (Table 2-5) are as before, and the demands for products in the first 30 days are the same as in Case Study 2. In order to apply the rolling horizon approach, they have been considered demands for products for 14 additional time periods (i.e., until day 44) which follow similar a distribution as in the previous periods. Minimum runtime and shutdown times are the same as in the previous examples. Here, all utility and production units are subject to condition-based cleaning, for which there are three alternative cleaning tasks options as before. There is a limited number of available cleaning resources equal to 12 units of cleaning resources. The parameters that refer to condition-based offline and online cleaning are defined in Table 2-8 are: (i) extra energy consumption limit ( $v_i^{max}$ ); (ii) performance degradation rate ( $\delta_i$ ); (iii) performance coefficient related to operating level ( $\delta_i^{cd}$ ); (iv) minimum time



between two consecutive online cleaning tasks ( $\gamma_i^{on}$ ); (v) recovery factor of the online cleaning ( $\rho_i^{rec}$ ); (vii) reduction factor of the operating level for online cleaning ( $\pi_i^{on}$ ); and (vi) resource requirement for online cleaning of a unit ( $\vartheta_i^{on}$ ). In addition, the parameters that define the initial state for this case study are given in Table 2-9. Terminal constraints for each prediction horizon are the same as in the previous case study.

**Table 2-8 Case Study 3: Parameters related to the condition-based cleaning of utility and production units**

Parameter	<i>i1</i>	<i>i2</i>	<i>i3</i>	<i>i4</i>	<i>i5</i>	<i>i6</i>	<i>i7</i>	<i>i8</i>
$v_i^{max}$	162	153	247	200	210	240	242	247
$\delta_i$	9	9	13	10	10	12	11	13
$\delta_i^{cd}$	6.75	6.75	9.75	7.50	7.50	9	8.25	9.75
$\gamma_i^{on}$	10	10	10	10	10	10	10	10
$\rho_i^{rec}$	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
$\pi_i^{on}$	0.05	0.05	0.05	0.05	0.05	0.10	0.10	0.10
$\vartheta_i^{on}$	1	1	1	1	1	1	1	1

**Table 2-9 Case Study 3: Initial state of utility and production units**

Parameter	<i>i1</i>	<i>i2</i>	<i>i3</i>	<i>i4</i>	<i>i5</i>	<i>i6</i>	<i>i7</i>	<i>i8</i>
$\tilde{\rho}_i$	9	16	17	4	18	8	5	17
$\tilde{\gamma}_i^{on}$	22	10	25	41	43	14	39	6
$\tilde{\omega}_i$	9	6	17	0	0	8	0	22
$\tilde{\psi}_i$	0	0	0	28	9	0	29	0
$\tilde{\rho}_i^{cd}$	0	0	0	0	0	0	0	0
$\tilde{\beta}_{(e1,z1)}$	60	units	Initial inventory for utility resource <i>e1</i>					
$\tilde{\beta}_{(e2,z2)}$	93	units	Initial inventory for utility resource <i>e2</i>					
$\tilde{\beta}_{(e3,z3)}$	132	units	Initial inventory for product resource <i>e3</i>					
$\tilde{\beta}_{(e4,z4)}$	56	units	Initial inventory for product resource <i>e4</i>					

### 2.6.3.2 Results of Case Study 3 – Integrated Approach

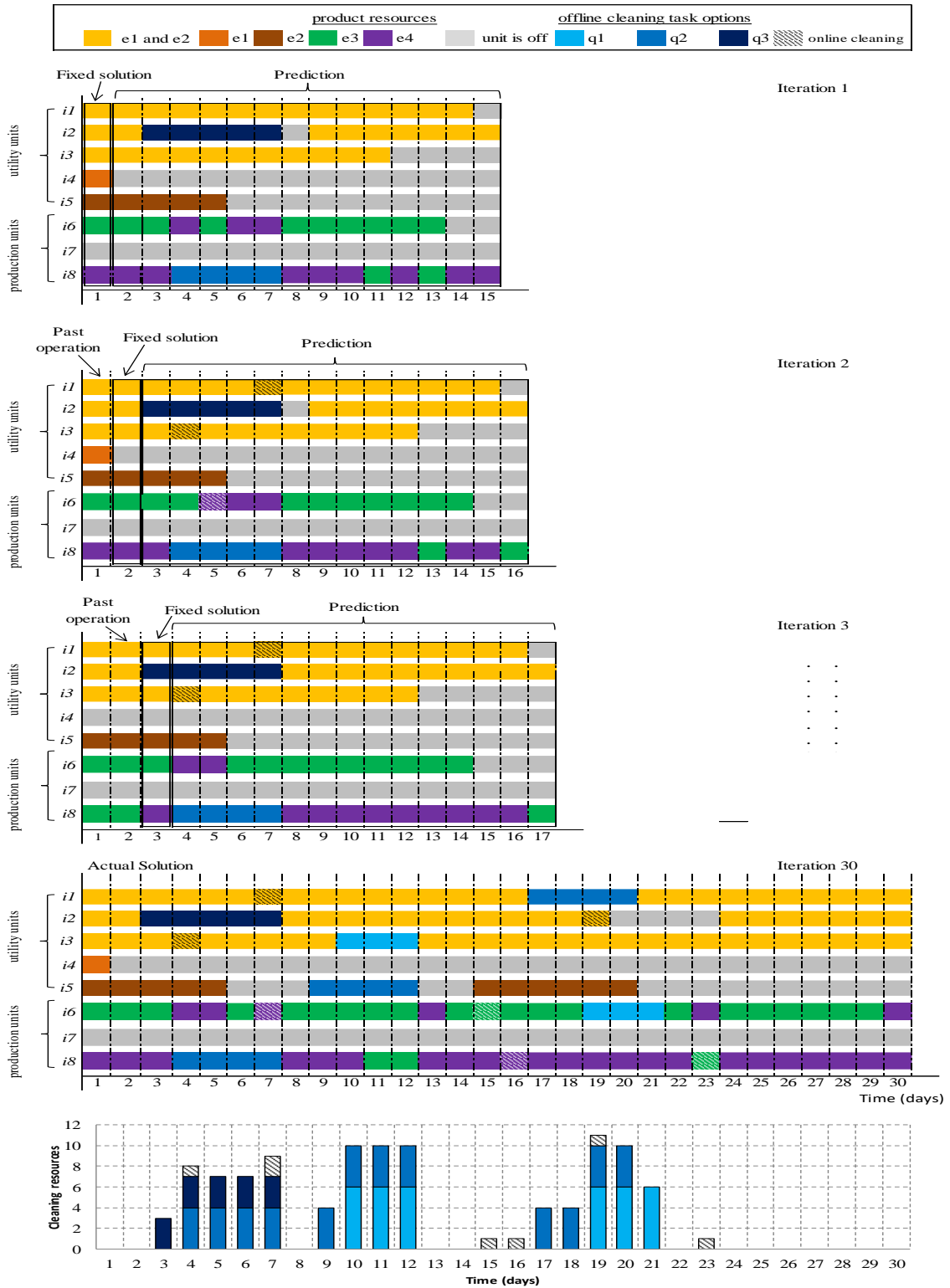
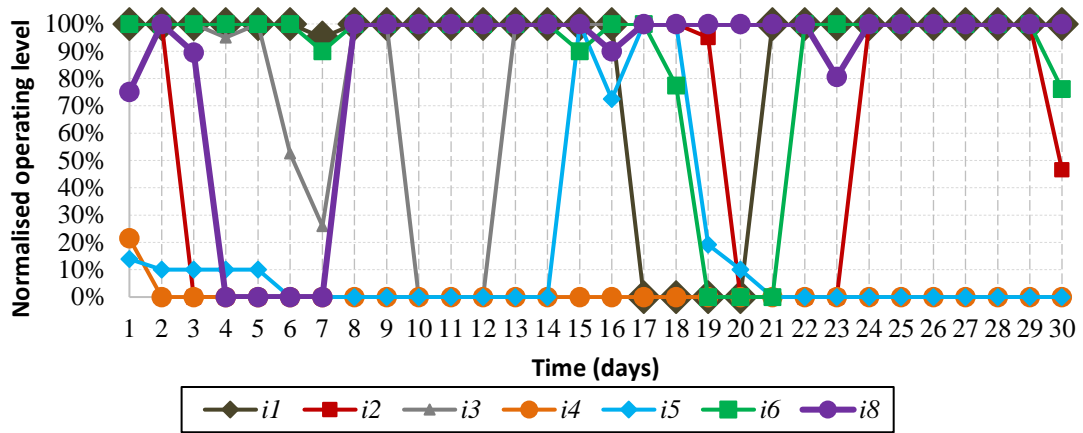


Figure 2-28 Case Study 3 - Rolling Horizon Integrated Approach: Plan generation via rolling horizon and total utilisation profile of cleaning resources

Figure 2-28 displays how the final plan for the 30-day horizon is constructed through the solution obtained from each iteration (an example of the first three iterations is included). The last Gantt chart in this figure gives the implemented operational and cleaning plan and the total utilisation profile of cleaning resources for the planning horizon considered.

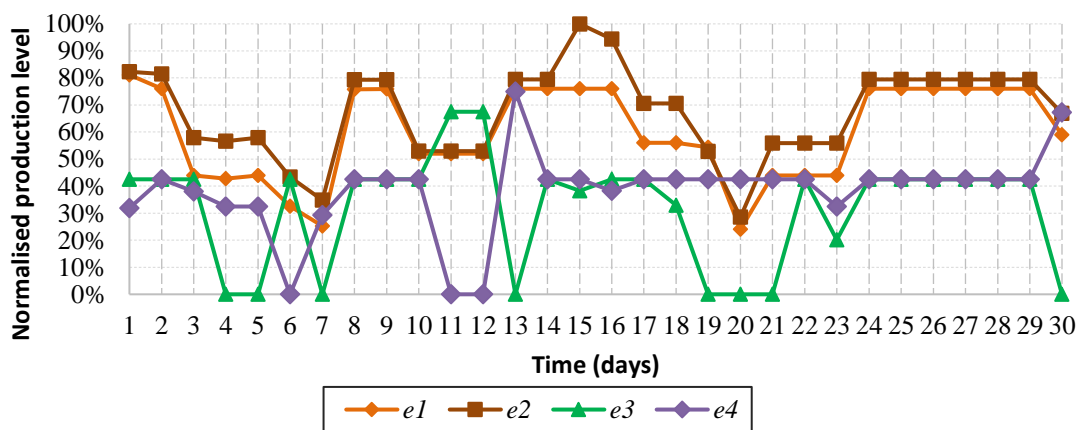
For the first iteration, the planning problem is solved for time periods 1 to 15. Only the solution of the first time period is saved. In the second iteration, a new optimisation problem for time periods 2 to 16 is solved having as initial state of the system the past solution for the first time period of the previous iteration. And, the rolling horizon method continues until all 30 iterations are solved (see also Figure 2-3).

Six offline and seven online cleaning tasks for utility and production units are observed in the implemented Gantt chart. There are some simultaneous condition-based offline cleaning tasks for some units, as listed below: (i) utility unit  $i2$  and production unit  $i8$  from day 4 and 7; (ii) utility units  $i5$  and  $i3$  from days 10 and 12; and (iii) utility unit  $i1$  and production unit  $i6$  in days 19 and 21. In addition, simultaneous online cleanings is observed for utility unit  $i1$  and production unit  $i6$  in day 7. Utility unit  $i4$ , which can only produce utility resource  $e1$ , operates just in day 1 because utility resource  $e1$  has enough supply from the utility units that can cogenerate both utility resources. Utility unit  $i5$ , which can produce utility resource  $e2$ , operates for two short-duration period, from day 1 to 5 and from day 15 to 20, because utility units  $i2$  and  $i1$  are closed for offline cleaning in some of these days. It is also observed that production unit  $i7$  remains idle for the whole planning horizon, because the demand for product resources is fully satisfied by the other production units.



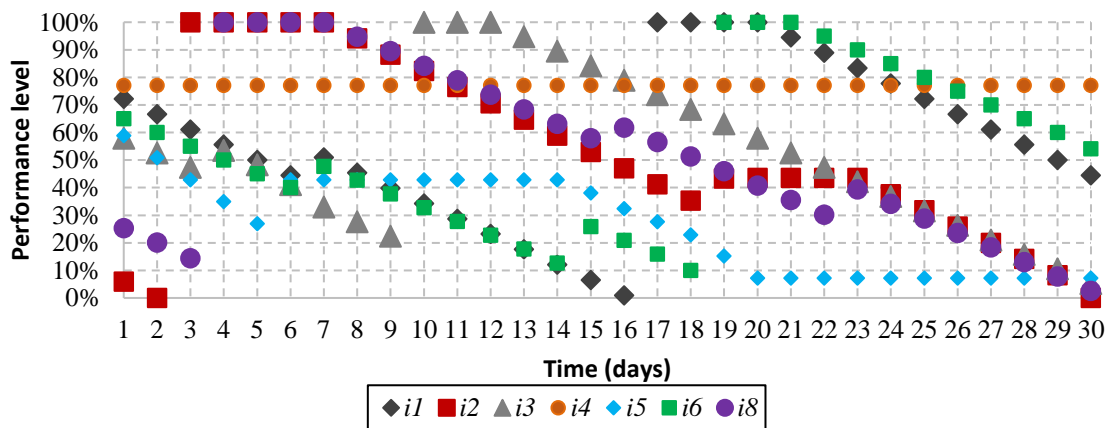
**Figure 2-29 Case Study 3 - Rolling Horizon Integrated Approach: Normalised operating level profiles for utility and production units**

The normalised operating level profiles for all units are displayed in Figure 2-29. In the utility system, utility units *i1* to *i3* operate at their maximum operating levels throughout the planning horizon (excluding their cleaning periods). Utility unit *i5*, which can generate only utility resource *e2*, operates in a shorter operating range to satisfy the varied needs for utility resource *e2*. In the production system, production units *i6* and *i8* operate at their maximum operating levels almost in all time periods to satisfy the high demand for product resources.



**Figure 2-30 Case Study 3 - Rolling Horizon Integrated Approach: Normalised total production profiles for utility and product resources**

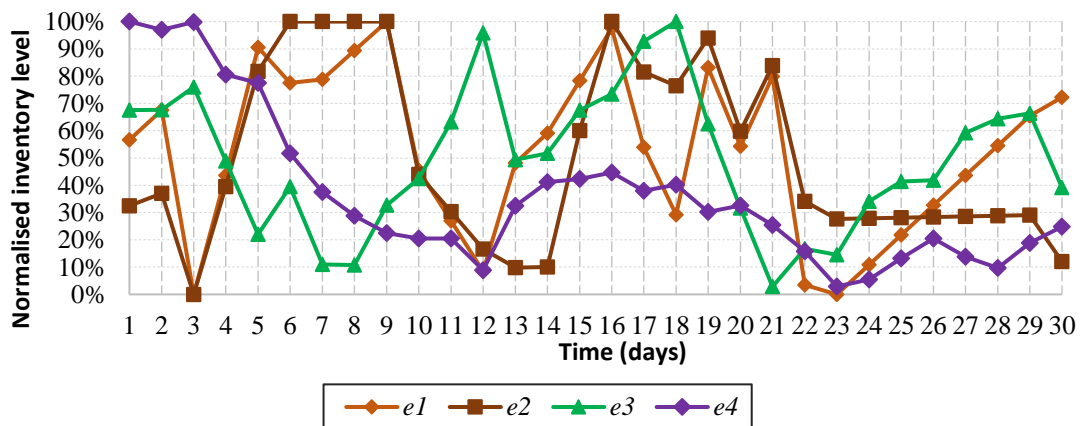
Figure 2-30 depicts the normalized total production profiles for each utility and product resource. The production of each resource is calculated by having the cumulative production of the resource from each unit divided by the maximum total resource production capacity of all units. Similar production trends are observed for utility resources  $e1$  and  $e2$  mainly due to the presence of three utility units that cogenerate both utility resources. The only differences are observed when utility unit  $i5$  operates from day 1 to 5 and from day 15 to 20. There are higher production differences of utility resource  $e2$  in comparison to utility resource  $e1$ . Meanwhile, the production levels for product resources  $e3$  and  $e4$  from day 8 to 10 and from day 24 to 29 are exactly the same because the upper operating level of utility unit  $i6$  that produces product resource  $e3$  and the upper operating level of production unit  $i8$  that produces product resource  $e4$  in these days are the same (refer to Table 2-1). In addition, when there is no production of product resources in some time periods (e.g., days 4, 5, 7, 13, 19, 20, 21 for product resource  $e3$  and days 6, 11, 12 for product resource  $e4$ ), the demands for product resources are fully satisfied through the inventory tanks for product resources.



**Figure 2-31 Case Study 3 - Rolling Horizon Integrated Approach: Performance level profiles for utility and production units per time period**

The performance level profiles for utility and production units are displayed in Figure 2-31. It is observed that utility unit  $i1$  undergoes online cleaning in day 7 to partially recover its performance and it continues operating until reaching its

critical performance level in day 16. The next day, utility unit *i1* is closed for offline cleaning in order to completely restore its full performance (i.e., clean condition). Production unit *i6* undergoes two online cleanings (in day 7 and 15) and an offline cleaning in day 19. Utility unit *i5* shows increased performance degradation from day 14 to 20 due to variation from its reference operating level (refer to Figure 2-29). It is also observed that utility unit *i5* reaches a very low performance level and eventually shuts down in day 21. No cleaning task takes place in this unit because it remains idle for the remaining planning horizon. In Figure 2-31, the performance levels of some operating units in day 30 are below 25% (i.e., terminal constraint) but this is not a violation of the corresponding terminal constraints. The solution of day 30 (including performance level values) has been derived from iteration 30 by solving a planning problem from time period 30 to time period 44, satisfying the terminal constraints for time period 44. In other words, in iteration 30, the terminal constraints apply for the last time period of the planning problem solved (i.e., day 44) and not for the first time period which is day 30.



**Figure 2-32 Case Study 3 - Rolling Horizon Integrated Approach: Normalised inventory profiles for utility and product resources**

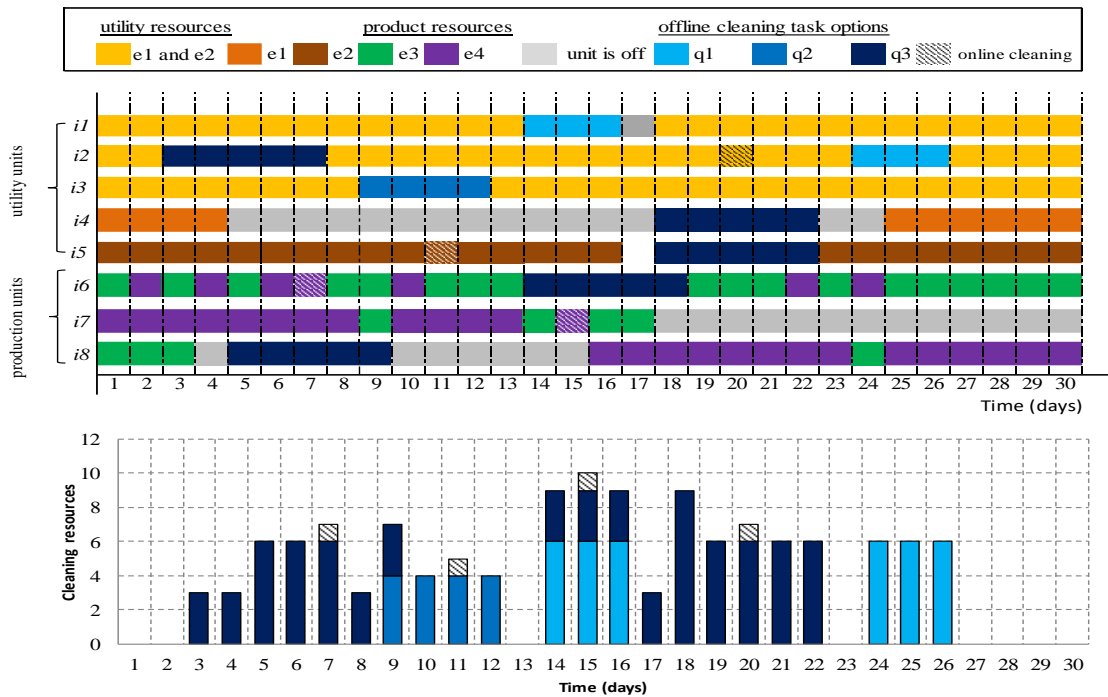
Figure 2-32 displays the normalised inventory profiles for utility and product resources, having as reference the associated maximum inventory levels. The high inventory level for utility and product resources at the first period is due to the high initial inventory levels. There are reduced inventory levels for utility

resources from day 10 to 12 and from day 16 to 18 due to the offline cleaning of some utility units that takes place in these days (see Figure 2-28). The inventory levels for product resources are reduced on day 4 to 7 and day 19 to 21 because of offline cleanings for production units. Recall that all inventory tanks are subject to terminal constraints that force the inventory levels in the last time period of each iteration to be 25% of the maximum capacity of the corresponding inventory tank. According to Figure 2-32, the inventory level for utility resource  $e2$  in day 30 is below 25% but this is not a violation of the terminal constraints. The solution of day 30 (including the inventory level values) has been derived from iteration 30 by solving a planning problem from time period 30 to time period 44, satisfying the terminal constraints for time period 44.

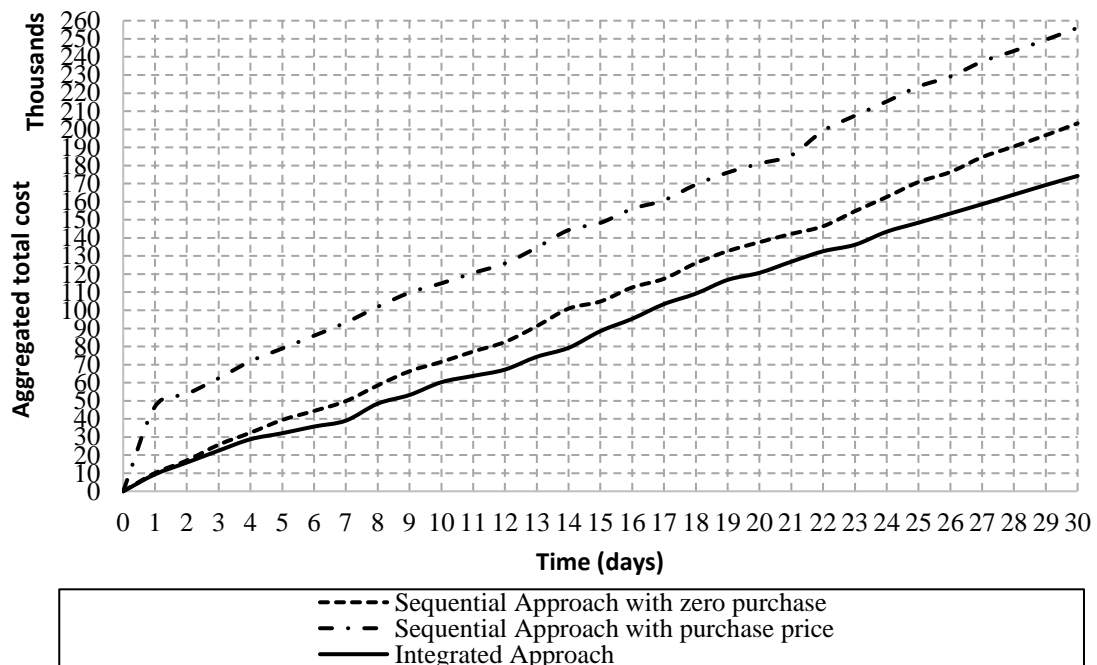
### **2.6.3.3 Results of Case Study 3 – Sequential Approach**

The same case study has been solved using the sequential approach to make a comparison between its solution with the solution obtained by the integrated approach. This case study requires in average of 60 seconds of CPU time for each optimisation problem.

Figure 2-33 displays the final Gantt chart and total utilisation profile of cleaning resources for the sequential rolling horizon approach. In comparison with the integrated approach, a higher number of offline and online cleaning tasks for utility units is observed. Utility units  $i4$  and  $i5$  operate in a larger number of time periods than before. Also, production unit  $i7$  is utilised in this case, while in the solution from the integrated rolling horizon approach was inactive for the whole planning horizon (see Figure 2-28). Here, production unit  $i7$  operates at the first half of the planning horizon and production unit  $i8$  operates mostly at the second half of the planning horizon. This solution also reports a highly increased number of production changeovers in the production units, which in practice can make more complicate the implementation of this plan.



**Figure 2-33 Case Study 3 - Rolling Horizon Sequential Approach: Operational and cleaning plan for production and utility systems and total utilisation profile of cleaning resources**



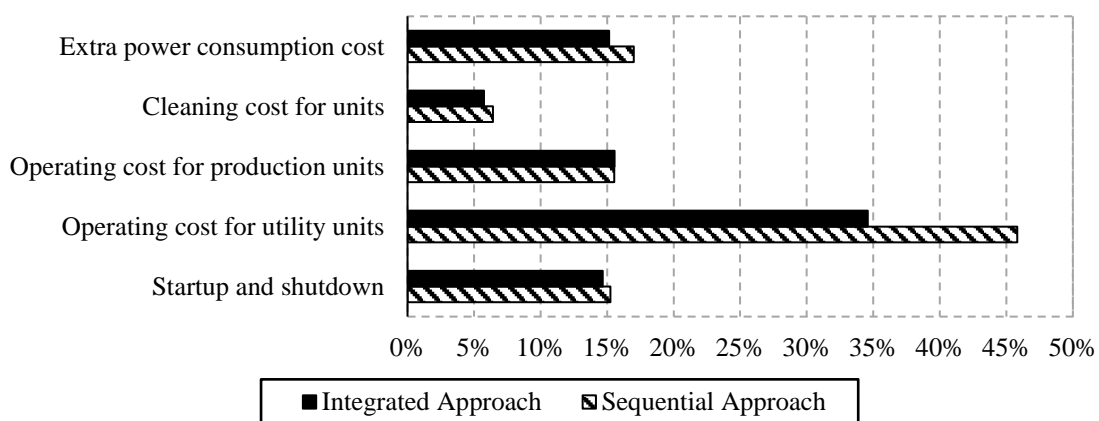
**Figure 2-34 Case Study 3: Aggregated total cost for integrated and sequential rolling horizon approaches**



Figure 2-34 displays the aggregated total cost for the integrated and the sequential rolling horizon approach. The total cost of the integrated approach is 14% lower than that of the sequential approach if a zero purchase price is considered, and 32% lower than that of the sequential approach if a purchase price equal to 200 is considered. The results clearly show that the integrated approach can find solutions that are better than those of the sequential approach, even if a zero purchase price is considered. In practice, penalty or real costs for acquiring utilities from external sources can be very high, since either represent an undesired managerial policy (i.e., dependency on external sources) or high-cost utilities. In this example, the solution following the sequential approach reports a total of 263.8 units of utility resource  $e_2$  that need to be purchased from external sources, as shown in Table 2-10.

**Table 2-10 Case Study 3 - Rolling Horizon Sequential Approach: Utilities purchases**

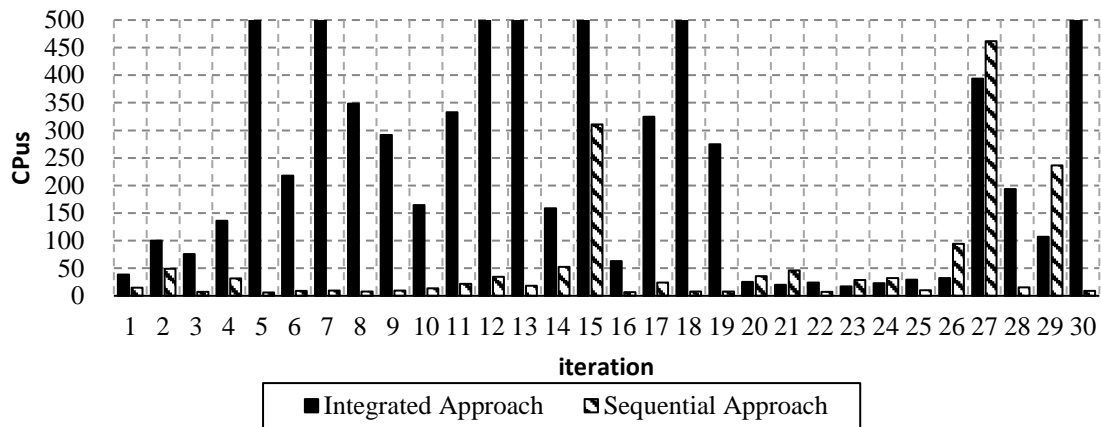
Utility Resource	Amount per time period (in metric units)					Total (in metric units)
	day 1	day 4	day 6	day 7	day 22	
$e_2$	183.6	13.9	10.4	9.2	46.8	263.8



**Figure 2-35 Case Study 3: Cost comparison of integrated and sequential rolling horizon approaches**

Figure 2-35 shows the cost comparison of the solutions derived by following the integrated and the sequential rolling horizon approach. Note that this figure does

not include the purchase cost for resources. As in the previous case study, the highest difference is observed in the operating cost for utility units by about 11%. Extra energy consumption cost difference is at 2%. The cleaning cost and startup and shutdown cost report both a difference of around 0.6%. The operating cost for production units is almost the same for both approaches.



**Figure 2-36 Case Study 3: CPUs values per iteration for integrated and sequential rolling horizon approaches**

Figure 2-36 shows the CPUs values of each iteration for both approaches. In most of the iterations, the integrated approach shows much higher CPUs values than the sequential approach. The average computational times for the sequential and the integrated approach are 53.9 and 389 CPUs, respectively. It should be clear that the integrated planning problem results in a more complex optimisation problem than the sequential planning problem, and therefore higher computational times would be observed for the resolution of the same planning problem. In Figure 2-36, one can observe that in some iterations, such as iteration 27 and 29, the computational time of the sequential approach is higher than that of the integrated approach. This is due to the fact that the two approaches may not solve exactly the same problem at each iteration (apart from the first iteration), since the planning problem under optimisation at each operation depends strongly on the initial state of the system, which in the rolling horizon framework is an optimisation output of the previous iteration (apart from the first iteration). Considering the complexity of the integrated planning problems solved in each

iteration, the integrated approach reported a very good computational performance.

## **2.7 Conclusions**

In this study, a rolling horizon optimisation framework has been developed for the integrated condition-based planning of utility and production system under uncertainty. Performance degradation and recovery has been considered for both systems. A number of representative case studies showed that the proposed integrated approach can provide significantly better solutions (compared to solutions obtained by sequential approaches) in terms of total costs, and especially in cost terms related to utility units operation, extra energy consumption, cleaning and startup/shutdown operations. The improved unit performance degradation and recovery models that depend on both the cumulative time of operation and the unit operating levels deviation of units have been developed. In the case studies solved, it is observed that the total cost of the solution of the integrated approach is lower than that of the solution of sequential approach within a range of 5% to 32%. This significant reduction in total costs is a direct result of the enhanced energy efficiency of the overall system through the optimised use and consumption of energy (i.e., major parts of the objective function). It has also been demonstrated that unnecessary purchases of resources can be avoided by the proposed integrated approach through the more efficient operation of utility units and the improved utilisation handling of energy and material resources. Overall, the proposed approach can result in a cleaner production since energy generation and consumption along with cleaning operations plans (source of waste sources) are optimised. In the longer term this could result in a sustainable production practices.

# **3 MIXED-INTEGER PROGRAMMING (MIP)-BASED DECOMPOSITION STRATEGY FOR SCHEDULING OF MULTISTAGE PRODUCTION SYSTEM AND COMBINED HEAT AND POWER**

## **3.1 Abstract**

An efficient decomposition strategy for solving scheduling problem of multistage production system and combined heat and power system is presented to investigate the potential of enhanced energy use through total costs reduction with relatively low computational effort. Although the integrated approach to optimise the production and utility system simultaneously can guarantee optimal solutions, extensive computational time is usually required. In addition, this is not practical for solving real scheduling problems due to urgent need to send the scheduling information to the production floor in a real time period. In this work, the integrated optimisation framework is decomposed into three stages of scheduling which are then solved consecutively through fixing and transferring certain variables to further reduce the computational time. The computational results show that the proposed three-stage decomposition strategy can achieve best solution and a zero optimality gap at faster computational time by an average magnitude of 4 than that of the integrated approach. A sensitivity analysis with respect to alternative emissions caps is also presented to show possible reduction of 1.2% in total emissions. Overall, the proposed three-stage MIP-based decomposition strategy could be used as an intermediary approach that combines the significant benefits of faster computational time of sequential approach with greater productivity offered by the integrated approach. In addition, efficient decomposition strategy is needed to produce high quality scheduling solutions that can significantly improve energy generation and utilisation of the production and utility systems.

## **3.2 Introduction**

Worldwide energy consumption is projected to rise 28% between 2015 and 2040, at an average annual energy growth rate of 1.1%. That in the industrial sector will

rise by 0.7% per year during the same period (EIA, 2017). The process industries consume a significant amount of primary sources of energy such as oil, coal and natural gas for the generation of utilities. The utilities can be in various forms such as pressurised steam, electricity, compressed air, or water. The dependency on the primary sources of energy in the process industries is the main environmental impact factor contributing to global warming due to the emissions of greenhouse gases, which are released to the environment during combustion processes. Therefore, efficient methods for reducing energy usage in the process industries, that result in cleaner production environments, can be achieved through the combination of process integration, monitoring and optimisation (Klemeš, Varbanov and Huisingh, 2012). For this reason, previous work has focused on development of a general optimisation framework for the integrated planning of production and utility systems in process industries that accounts for efficient generation and consumption of energy, and improved utilisation of material resources (Zulkafli and Kopanos, 2016, 2017).

Industrial plants in the process industries are generally composed of production and utility systems. The major utility systems in industrial plants are known as combined heat and power (CHP). The CHP-based utility system is an important energy generation technology as it is characterised with a higher total efficiency and reduced carbon dioxide (CO<sub>2</sub>) emissions than that of other types of utility systems (Klemeš, Varbanov and Kravanja, 2013). Therefore, many industrial plants, such as chemical and petrochemical plants, have the CHP-based utility system installed onsite to simultaneously generate electricity and pressurised steam to satisfy the utility requirements of their production systems. Meanwhile, the production systems can be further classified as continuous or batch. In batch production systems, the main scheduling problems are the allocations of multi-stage production with multiple steps and complex routings to produce final products in batches. Sundaramoorthy, Maravelias and Prasad (2009) proposed scheduling of multistage batch production under utility constraints. Then Sundaramoorthy (2010) presented a unified representation for sequential and network processes in batch production system. The special features of the

proposed model were the characterisation of states and tasks of the batch subsystems, expression of sequential subsystems using a material-based approach and enforcement of batch integrity in sequential subsystems. In addition, the classification of optimisation models for scheduling of batch production systems was explored by Méndez et al. (2006).

The traditional optimisation approach to solve the scheduling of two interconnected systems is a sequential approach. In this approach, the scheduling of a production system is first derived to obtain information regarding utility requirements. Then the scheduling of the utility system is solved to satisfy the utility demand of the production system. The sequential approach favours the production system while treating the utility system as its subsidiary system (Sahni, 1996). It has become apparent that the sequential approach focuses on emphasising only the effective scheduling of the production system while purposely ignoring the operational capability of the utility system, resulting in inefficient use of the generated utilities. As a means of efficient energy generation and utilisation, the scheduling of production and utility systems should be fully integrated in the optimisation framework. There is little research that deals with the integrated optimisation framework of the CHP-based utility system and the production system. Perkovi et al. (2017) analysed the potential of cost reduction of a production facility that consisted of CHP and a production facility under a day-ahead electricity market. The result showed that the operational cost was reduced by the optimisation of the power flows within the production facility. Celma et al. (2013) performed a feasibility analysis to investigate the potential of installing a CHP system in an industrial olive production system. The olive processing plant reported a reduction in the energy demand by more than 40% compared to conventional utility supplies through the use of steam boilers and electricity purchase. The analysis also showed a simple payback period of 3.6 years. In addition, other works on extended resource task network (ERTN) for scheduling batch production systems and CHP plants have been presented (Agha et al., 2009; Théry et al., 2012). Although ERTN formulation is simple to implement in addressing scheduling problems, the interconnection between the

two systems must be completely understood to properly address the resulting scheduling problems.

The new approach that deals with simultaneous planning of production and utility systems is known as an integrated approach (Zulkafli and Kopanos, 2016, 2017). In previous work, the proposed integrated approach provides significantly better solutions compared to solutions obtained by the sequential approach in terms of total costs. However, the major challenges to solve integrated planning and scheduling problems are the development of computationally efficient formulations especially for solving complex industrial scheduling. Decomposition approaches have been proposed for an effective method that exploits the structure of the optimisation framework to solve hard-constrained optimisation problems with relatively low computational efforts (Maravelias and Sung, 2009).

Therefore, the focus of this study is on the method of MIP-based decomposition strategy to solve the scheduling problems of multistage production system and CHP-based utility system at relatively low computational performance than that of the integrated approach.

This chapter is organised as follows. Section 3.3 provides a brief literature review. The formal statement of the problem under study is defined in Section 3.4. The optimisation framework is presented in Section 3.5, followed by the description and discussion of the computational experiments and a case study in Section 3.6. Finally, concluding remark is provided in Section 3.7.

### **3.3 Literature Review**

Most of the previous studies in literature have used different methods of decomposition approaches to address separately the scheduling problems of production systems or the scheduling problems of the utility systems. The works that addressed decomposition approaches only for the scheduling problems of production systems are the following. Wu and Ierapetritou (2007) studied hierarchical decomposition approach for solving multi-stage production planning and scheduling. An iterative framework through a rolling horizon strategy was developed to save the planning and scheduling results before solving for the next

iteration. Kopanos, Méndez and Puigjaner (2010) proposed MIP-based decomposition strategy as an efficient iterative solution for solving large-scale scheduling problems in multiproduct multistage batch plants. Wei and Guimar (2014) proposed MIP-based decomposition method to solve two-stage production and distribution scheduling problems.

Other works focused only on the methods of decomposition approaches to solve the scheduling problems of utility systems. For example, Abdolmohammadi and Kazemi (2013) studied benders decomposition based approach to solve economic dispatch scheduling problems for cogeneration systems. Sadeghian and Ardehali (2016) proposed scheduling of integrated combined heat and power system with conventional thermal power units based on benders decomposition strategy to maximise profit and minimise emissions. There are few works that address the planning of production and utility system and the use of decomposition method. For example, Zhao, Rong and Feng (2015) proposed an effective solution approach for integrated scheduling of refinery production and utility system. The integrated model was decomposed into an MILP model and NLP model that was solved iteratively. The MILP model solution of sequential approach was used to obtain feasible solution for solving the NLP model in the following steps.

However, the main drawback of decomposition approach is that the optimality may not be accomplished due to both systems are not optimised simultaneously. The nature of highly complicated and dynamic industrial environment results to large MIP model, which is often computationally intractable. Furthermore, difficult scheduling problems that require extensive computational time in integrated approach to reach optimality is not practical for many process industries because the scheduling information must be send to the production floor in a real time period for effective demand management (Grossmann, 2005).

It is clear from the above discussion that an effective decomposition approach is needed for addressing efficient scheduling in a process industry. Furthermore, the proposed decomposition strategy combines the salient features of faster computational time of sequential approach and superior productivity (e.g.,



enhanced energy and total costs reduction) offered by the integrated approach. This chapter presents a three-stage MIP-based decomposition strategy to solve integrated planning problem of production and utility systems in order to achieve optimal or near-optimal solution at faster computational time than that of the integrated approach. The integrated optimisation framework consists of the scheduling model of multistage production system introduced by Velez and Maravelias (2013), combined in with the model for CHP-based utility system (Agha et al., 2010) and also units degradation and recovery model from the previous chapter (i.e., Chapter 2). This is the first work that addresses simultaneous operational and cleaning scheduling of the multistage production system and CHP-based utility system that relies on effective decomposition strategy to achieve the best possible schedules with relatively low computational time.

### 3.4 Problem Statement

This work focuses on the integrated operational and cleaning schedule of multistage production system and CHP-based utility system. The production system considers product resource-constrained batching policies. For example, the separate batches of a no-mixing product resource cannot be combined, and a single batch of a no-splitting product resource cannot be separated into multiple product batches. The scheduling model is decomposed into three-stage MIP-based decomposition strategy. This scheduling problem is formally defined in terms of the following items:

- A given planning horizon divided into one-hour time periods  $t \in T$ .
- A set of utility, product and emission resources  $e \in E$  that are classified to intermediate and final product ( $e \in E^{PR}$ ), utility resources ( $e \in E^{UT}$ ), fuel resources ( $e \in E^{FUEL}$ ) and emissions ( $e \in E^{EMIS}$ ). The intermediate and final product is associated to resource-constrained for which batch splitting ( $e \in E^{NS}$ ) or mixing ( $e \in E^{NM}$ ) is not allowed. The utility resources are classified to high pressure (HP) steam ( $e \in E^{HP}$ ), medium pressure (MP) steam ( $e \in E^{MP}$ ), low pressure (LP) steam ( $e \in E^{LP}$ ) and electricity ( $e \in E^{EL}$ ).

- A set of units  $i \in I$  that are classified to utility units ( $i \in UT_i$ ), production units ( $i \in PR_i$ ), inventory tanks ( $i \in ZI_i$ ) and customers ( $i \in CS_i$ ). The utility units consist of a number of boilers ( $i \in I^{BL}$ ) and turbines ( $i \in I^{TB}$ ). The production units could consume or produce a number of product resources ( $i \in I_e^-$  or  $i \in I_e^+$ ). The inventory tanks could store product resources ( $i \in IT_e$ ). Maximum (minimum) operating capacities  $\beta_i^{max}$  ( $\beta_i^{min}$ ) for utility and production units are known. The final products for each customer have known demand  $\zeta_{(e,i)}$ .
- A set of production task  $j \in J_i$  that could consume or produce a number of product resources ( $j \in J_e^-$  or  $j \in J_e^+$ ). For every task, the processing time  $\tau_{(i,j)}$  and conversion coefficient  $\rho_{(e,j)}$  are given.
- A set of piecewise segment of efficiency curve  $p \in P$  to determine the amount of fuel that can be consumed by the boiler  $i \in I^{BL}$  to produce HP steam.
- For every utility resource  $e \in E^{UT}$ , fixed and variable utility requirements for the production units in each task are given ( $\bar{\alpha}_{(j,i,e)}$  and  $\alpha_{(j,i,e)}$ , respectively).
- A set of condition-based cleaning  $i \in CB_i$  with known performance degradation rates  $\delta_i$  and performance coefficient of cumulative deviation from its reference operating level  $\delta_i^{cd}$ . Two types of condition-based cleaning tasks are considered namely online cleaning  $CB_i^{on}$  with given recovery factors  $\rho_i^{rec}$ , and offline cleaning  $CB_i^{off}$ .
- A set of alternative offline cleaning tasks options  $q \in Q_i$  for each unit that is subject to condition-based cleaning  $CB_i^{off}$  that are characterised by different durations  $\nu_{(i,q)}$ , cleaning resources requirement  $\vartheta_{(i,q)}^{off}$ , and associated cleaning costs  $\phi_{(i,q,t)}^{off}$ .

- Given variable and fixed operating costs for production units,  $\phi_{(j,i)}^{PR,var}$  and  $\phi_{(j,i)}^{PR,fix}$ , respectively and utility units in CHP system,  $\phi_{(i,t)}^{BL,var} / \phi_{(i,t)}^{TB,var}$  and  $\phi_{(i,t)}^{BL,fix} / \phi_{(i,t)}^{TB,fix}$ , respectively.
- Given purchase prices for acquiring utility resources from external sources,  $\phi_{(e,t)}^{UT,ex}$ .
- Given fuel cost for boilers,  $\phi_e^{FUEL}$  inventory cost for production units  $\phi_{(e,i)}^{STOR}$  and emissions cost  $\phi_e^{EMIS}$ .
- A given time-varying energy price profile  $\phi_{(i,t)}^{pw}$ .

For every time period, the key decisions to be made by the optimisation model are:

- the operational status for each production and utility unit (i.e., startup, shutdown, in operation, idle);
- the operating level for each production and utility unit;
- the inventory level for each inventory tank of fuels and product resources;
- the utility requirements for each task of production units;
- the selection of the timing and the types of the cleaning tasks to be performed in each unit under condition-based cleaning;
- the batch sizes and timing for each task of production units; and
- the selection of timing for order delivery of final products to customers.

All these with the goal to minimise total cost of the overall system which includes:

- fixed and variable operating costs for production and utility units;
- startup and shutdown costs for the utility units;
- storage costs for the inventory tanks of production resources;
- fuel consumption costs;
- extra energy costs due to performance degradation for units under condition-based cleaning tasks
- cleaning costs for units under condition-based cleaning tasks;
- penalty costs for acquiring utility resources from external sources; and

- penalty costs for emissions of greenhouse gas and SOx.

### 3.5 Optimisation Framework

A linear MIP model is presented for the integrated scheduling problem considered in this study. The proposed optimisation model follows three-stage MIP-based decomposition strategy to solve integrated planning problems of multistage production system and CHP-based utility system with relatively low computational efforts. A description of the proposed optimisation framework follows.

#### 3.5.1 Multistage Production System

##### 3.5.1.1 Unit Balance Constraints

To model the unit balance constraints of the production system, the following set of binary variables is introduced:

$$X_{(i,t)} = \begin{cases} 1 & \text{if production unit } i \text{ is operating during time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$XS_{(i,t)} = \begin{cases} 1 & \text{if inventory tank } i \text{ is operating during time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$XP_{(i,j,t)} = \begin{cases} 1 & \text{if production unit } i \text{ is processing task } j \text{ starting at time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$XZ_{(e,i,t)} = \begin{cases} 1 & \text{if inventory tank } i \text{ is storing material resource } e \text{ during time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

The unit balance of each production unit and inventory tank is modelled according to:

$$X_{(i,t)} = X_{(i,t-1)} - \sum_{j \in J_i} XP_{(i,j,t-\tau_{(i,j)})} + \sum_{i \in J_i} XP_{(i,j,t)} \quad \forall i \in PR_i, t \in T \quad (3-1)$$

$$XS_{(i,t)} = XS_{(i,t-1)} - \sum_{e \in \Pi_e} XZ_{(e,i,t-1)} + \sum_{e \in \Pi_e} XZ_{(e,i,t)} \quad \forall i \in ZI_i, t \in T \quad (3-2)$$

The first and second sets of constraints ensure that no production unit or inventory tank can process multiple tasks or store multiple product resources at the same time simultaneously.

### 3.5.1.2 Product Resources Transfer

The flow of product resources from a production unit to another production unit is modelled by the following constraints.

$$\begin{aligned}
\sum_{i' \in IC_i^- \cap I_e^+} FT_{(e,i',i,t)} &= \sum_{j \in J_e^- \cap J_i} -\rho_{(e,j)} BT_{(i,j,t)} & \forall e \in E, i \in I_e^- \cap PR_i, t \in T \\
\sum_{i' \in IC_i^+ \cap I_e^-} FT_{(e,i,i',t)} &= \sum_{j \in J_e^+ \cap J_i} \rho_{(e,j)} BT_{(i,j,t-\tau_{ij})} & \forall e \in E, i \in I_e^+ \cap PR_i, t \in T
\end{aligned} \tag{3-3}$$

The first set of constraints describe the inlet flow of a product resource to the production unit must be equal to the amount of product resource that is consumed by a task in that production unit. Similarly, the outlet flow of a product resource from the production unit must be equal to the amount of product resource that is produced by a task in that production unit. Parameter  $\rho_{(e,j)}$  is the conversion coefficient of product resource for each task.

The product resource balances for every resource-dedicated inventory tank per time period are given by:

$$\begin{aligned}
B_{(e,i,t)} &= \tilde{\beta}_{(e,i)} + \sum_{i' \in IC_i^- \cap I_e^+} FT_{(e,i',i,t)} - \sum_{i' \in IC_i^+ \cap I_e^-} FT_{(e,i,i',t)} & \forall e \in E, i \in IT_e, t \in T: t=1 \\
B_{(e,i,t)} &= B_{(e,i,t-1)} + \sum_{i' \in IC_i^- \cap I_e^+} FT_{(e,i',i,t)} - \sum_{i' \in IC_i^+ \cap I_e^-} FT_{(e,i,i',t)} & \forall e \in E, i \in IT_e, t \in T: t>1
\end{aligned} \tag{3-4}$$

Notice that variables  $B_{(e,i,t)}$  indicate the inventory level per product resource and inventory tank at the end of each time period and variables  $FT_{(e,i',i,t)}$  represent the inlet flow to the inventory tank and variables  $FT_{(e,i,i',t)}$  represent the outlet flow from the inventory tank. Parameters  $\tilde{\beta}_{(e,i)}$  stand for the initial inventory for each product resource inventory tank at the beginning of the scheduling horizon.

### 3.5.1.3 Batching Restriction for Product Resources

The following constraints enforce batching restriction when product resource is transferred between the production units. The batching restriction for product resources is modelled for the production units that consume or produce these product resources. In order to model the batching restriction for product resources, the following binary variables are introduced:

$$WT_{(e,i,i',t)} = \begin{cases} 1 & \text{if product resource } e \text{ is transferred from unit } i \text{ to unit } i' \text{ at time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

A no-splitting product resource is transferred from a production unit to at most one other unit are given by:

$$\sum_{i' \in IC_e^+ \cap I_e^-} WT_{(e,i,i',t)} \leq 1 \quad \forall e \in E^{NS}, i \in PR_i \cap I_e^+, t \in T \quad (3-5)$$

When the connection of no-splitting product resource between inventory tank and production unit takes place (i.e.,  $WT_{(e,i,i',t)} = 1$ ), the no-splitting product resources in the inventory tank at the previous time period must be equal to the outlet flow of no-splitting product resource from the inventory tank to another production unit at the current time period.

$$B_{(e,i,t-1)} - \max_{i' \in IC_e^+ \cap I_e^-} \xi_{(e,i,i')} \left( 1 - \sum_{i' \in IC_e^+ \cap I_e^-} WT_{(e,i,i',t)} \right) \leq \sum_{i' \in IC_e^+ \cap I_e^-} FT_{(e,i,i',t)} \leq B_{(e,i,t-1)} \quad \forall e \in E^{NS}, i \in ZI_i, t \in T \quad (3-6)$$

Parameter  $\xi_{(e,i,i')}$  is the maximum flow of product resources between the production units or inventory tanks that can be calculated according to:

$$\xi_{(e,i,i')} = \begin{cases} \min \left( \max_{j \in J_e^+ \cap J_i} (\rho_{(e,j)} \beta_i^{\max}), \max_{j \in J_e^- \cap J_{i'}} (\beta_{i'}^{\max}) \right) & \forall i \in PR_i, i' \in PR_i \\ \min \left( \beta_i^{\max}, \max_{j \in J_e^- \cap J_{i'}} (\beta_{i'}^{\max}) \right) & \forall i \in ZI_i, i' \in PR_i \\ \min \left( \max_{j \in J_e^+ \cap J_i} (\rho_{(e,j)} \beta_i^{\max}), \beta_{i'}^{\max} \right) & \forall i \in PR_i, i' \in ZI_i \\ \min(\beta_i^{\max}, \beta_{i'}^{\max}) & \forall i \in ZI_i, i' \in ZI_i \end{cases} \quad (3-7)$$

Parameter  $\beta_i^{\max}$  is the capacity of the production units or the inventory tanks.

A no-mixing product resource is transferred to a production unit from at most one other production unit as given by:

$$\sum_{i' \in IC_i^- \cap I_e^+} WT_{(e,i',i,t)} \leq 1 \quad \forall e \in E^{NM}, i \in PR_i \cap I_e^-, t \in T \quad (3-8)$$

When the connection of no-mixing product resource between production unit and the inventory tank takes place (i.e.,  $WT_{(e,i',i,t)} = 1$ ), the no-mixing product resource in the inventory tank at the current time period must be equal to the inlet flow of no-mixing product resource from the production unit to the inventory tank at that time period.

$$B_{(e,i,t)} - \max_{i' \in IC_i^- \cap I_e^+} \xi_{e,i',i} \left( 1 - \sum_{i' \in IC_i^- \cap I_e^+} WT_{(e,i',i,t)} \right) \leq \sum_{i' \in IC_i^- \cap I_e^+} FT_{(e,i',i,t)} \leq B_{(e,i,t)} \quad \forall e \in E^{NM}, i \in ZI_i, t \in T \quad (3-9)$$

### 3.5.1.4 Order Delivery

The following sets of constraints ensure that only one order is delivered to a customer for each final product resource. In addition, a customer can order multiple final products according to:

$$\sum_{t \in T} G_{(e,i,t)} = 1 \quad \forall e \in E^{PR}, i \in CS_i \quad (3-10)$$

The final product demand by the customer must be fully satisfied by the total flow of final products from production units to the customers as given by:

$$\zeta_{(e,i)} G_{(e,i,t)} = \sum_{i' \in IC_i^- \cap I_e^+} FT_{(e,i',i,t)} \quad \forall e \in E^{PR}, i \in CS_i, t \in T \quad (3-11)$$

### 3.5.1.5 Capacity Constraints

The no-mixing and no-splitting product resources can be transferred between two units only when a connection takes place.

$$FT_{(e,i,i',t)} \leq \xi_{(e,i,i')} WT_{(e,i,i',t)} \quad \forall e \in E^{NM} \cup E^{NS}, i \in I_e^+, i' \in IC_i^+ \cap I_e^-, t \in T \quad (3-12)$$

Meanwhile, product resources with no batching restrictions can always be transferred between units. The batch size of a task in a production unit must be

between the corresponding lower and upper bound of the capacities of the production unit as given by:

$$\beta_i^{\min} XP_{(i,j,t)} \leq BT_{(i,j,t)} \leq \beta_i^{\max} XP_{(i,j,t)} \quad \forall i \in I, j \in J, t \in T \quad (3-13)$$

The inventory level of product resources must be less than or equal to the maximum capacity of the inventory tank according to:

$$B_{(e,i,t)} \leq \varepsilon_i^{\max} XS_{(e,i,t)} \quad \forall e \in E, i \in I, t \in T \quad (3-14)$$

## 3.5.2 Combined Heat and Power Utility System

### 3.5.2.1 Startup and Shutdown Actions

In order to model the operational status of utility units (i.e., boilers and turbines), the following set of binary variables is introduced:

$$XE_{(e,i,t)} = \begin{cases} 1 & \text{if unit } i \text{ consumes or produces resource } e \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$SE_{(e,i,t)} = \begin{cases} 1 & \text{if unit } i \text{ consumes or produces resource } e \text{ starts up at the beginning of time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$FE_{(e,i,t)} = \begin{cases} 1 & \text{if unit } i \text{ consumes or produces resource } e \text{ shuts down at the beginning of time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

The operational status of each unit that is subject to startup and shutdown cost is modelled according to:

$$\begin{aligned} SE_{(e,i,t)} - FE_{(e,i,t)} &= XE_{(e,i,t)} - \tilde{\chi}_{(e,i)} & \forall e \in E^{FUEL} \cup E^{HP}, i \in I^{SF}, t \in T : t = 1 \\ SE_{(e,i,t)} - FE_{(e,i,t)} &= XE_{(e,i,t)} - XE_{(e,i,t-1)} & \forall e \in E^{FUEL} \cup E^{HP}, i \in I^{SF}, t \in T : t > 1 \\ SE_{(e,i,t)} + FE_{(e,i,t)} &\leq 1 & \forall e \in E^{FUEL} \cup E^{HP}, i \in I^{SF}, t \in T \end{aligned} \quad (3-15)$$

The first two sets of constraints show the connection of the startup and shutdown actions with the operating binary variables, while the last set of constraints ensure that startup and shutdown action cannot occur simultaneously.

The minimum runtime and shutdown time restriction for the unit are modelled as given by constraints (3-16) and (3-17), respectively:



$$\begin{aligned}
XE_{(e,i,t)} &\geq \sum_{t'=\max\{1,t-\omega_i+1\}}^t SE_{(e,i,t')} & \forall e \in E^{FUEL} \cup E^{HP}, i \in I^{S-min}, t \in T: \omega_i > 1 \\
\sum_{e \in (E^{FUEL} \cup E^{HP})} XE_{(e,i,t)} &= 1 & \forall i \in I^{BL} \cup I^{TB}, t = 1, \dots, (\omega_i - \tilde{\omega}_i): 0 < \tilde{\omega}_i < \omega_i
\end{aligned} \tag{3-16}$$

$$\begin{aligned}
1 - XE_{(e,i,t)} &\geq \sum_{t'=\max\{1,t-\psi_i+1\}}^t FE_{(e,i,t')} & \forall e \in E^{FUEL} \cup E^{HP}, i \in I^{F-min}, t \in T: \psi_i > 1 \\
\sum_{e \in (E^{FUEL} \cup E^{HP})} XE_{(e,i,t)} &= 0 & \forall i \in I^{BL} \cup I^{TB}, t = 1, \dots, (\psi_i - \tilde{\psi}_i): 0 < \tilde{\psi}_i < \psi_i
\end{aligned} \tag{3-17}$$

Parameters  $\tilde{\omega}_i$  ( $\tilde{\psi}_i$ ) describe the total number of consecutive operating (idle) time periods since its last startup (shutdown) at the beginning of the current scheduling horizon. In addition, a maximum runtime ( $o_i$ ) may be imposed for units  $i \in MR_i$  that do not follow a more detailed performance-based cleaning planning, according to:

$$\begin{aligned}
\sum_{t'=\max\{1,t-o_i\}}^t XE_{(e,i,t')} &\leq o_i & \forall e \in E^{HP}, i \in MR_i, t \in T \\
\sum_{t'=\max\{1,t-(o_i-\tilde{\omega}_i)\}}^t XE_{(e,i,t')} &\leq (o_i - \tilde{\omega}_i) & \forall e \in E^{HP}, i \in MR_i, t = (o_i - \tilde{\omega}_i + 1): \tilde{\omega} > 1
\end{aligned} \tag{3-18}$$

The maximum runtime of a unit is used to prevent major mechanical damages and improve energy efficiency of the unit when the method of performance degradation of the unit is not considered.

Although multi-fuel fired boiler is considered, only one type of fuel can be used during the startup and operation of the boiler according to:

$$\begin{aligned}
\sum_{e \in E^{FUEL}} XE_{(e,i,t)} &\leq 1 & \forall i \in I^{BL}, t \in T \\
\sum_{e \in E^{FUEL}} SE_{(e,i,t)} &\leq 1 & \forall i \in I^{BL}, t \in T
\end{aligned} \tag{3-19}$$

The amount of fuel consumed by the boiler without producing steam during the startup action is given by:

$$FS_{(e,i,t)} = fuel_{(e,i)}^s SE_{(e,i,t)} \quad \forall e \in E^{FUEL}, i \in I^{BL}, t \in T \tag{3-20}$$

### 3.5.2.2 Inventories for Fuel

The fuel balances in the fuel-dedicated inventory tanks are given by:

$$\begin{aligned}
 B_{(e,i,t)} &= \tilde{\beta}_{(e,i)} - \left( \sum_{i' \in I^{BL}} FT_{(e,i,i',t)} + FS_{(e,i',t)} \right) & \forall e \in E^{FUEL}, i \in IT_e, t \in T \\
 B_{(e,i,t)} &= B_{(e,i,t-1)} - \left( \sum_{i' \in I^{BL}} FT_{(e,i,i',t)} + FS_{(e,i',t)} \right) & \forall e \in E^{FUEL}, i \in IT_e, t \in T
 \end{aligned} \tag{3-21}$$

Variable  $FT_{(e,i,i',t)}$  represents the outlet flow of fuel that leaves its inventory tank so as to satisfy the corresponding requirement for fuel of the boiler to produce HP steam at each time period. Variable  $FS_{(e,i',t)}$  gives the amount of fuel that is consumed by the boiler during the boiler's startup without producing steam. Parameter  $\tilde{\beta}_{(e,i)}$  provides the initial inventory for each fuel inventory tank. Minimum and maximum inventory tanks are also given by:

$$\varepsilon_{(e,i)}^{\min} \leq B_{(e,i,t)} \leq \varepsilon_{(e,i)}^{\max} \quad \forall e \in E^{FUEL}, i \in IT_e, t \in T \tag{3-22}$$

### 3.5.2.3 Operational Constraints for Boilers

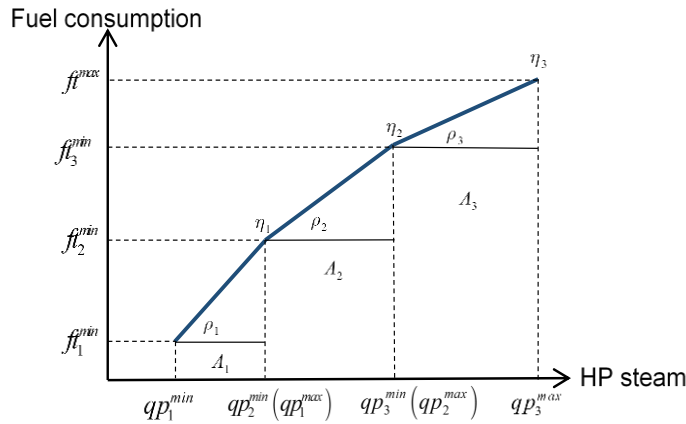
The main assumptions in the operational model for boiler are: (i) the boiler has an excess supply of air and water; (ii) only one type of fuel is consumed by the boiler during a time period; (iii) the steam pressures and temperatures are fixed at the boiler inlet and outlet. The boiler requires electricity to perform its operation, MP steam to pre-heat water and fuel where it is burnt to generate HP steam. The description of the model for the operation for boiler follows:

#### 3.5.2.3.1 Production of steam and its relation to fuel consumption

The fuel consumption in the boiler as a function of the amount of HP steam produced is given by the following equation:

$$ft_{(e,i,p)} = \frac{(h_b - h_{fw})qp_{(e,i,p)}}{cv_e \eta_{(e,i,p)}^{FUEL}} \quad \forall e \in E^{FUEL}, i \in I^{BL}, p \in P \tag{3-23}$$

Parameter  $h_b$  gives the enthalpy of superheated steam,  $h_{fw}$  gives the enthalpy of feed-water heaters and  $cv_e$  represents the calorific value of fuel. In order to maintain the linearity of the model, piecewise linear approximation is used to measure the fuel consumption with variation on the amount of steam produced and the effect of boiler's efficiency as shown in Figure 3-1.



**Figure 3-1 Correlation of fuel consumption and amount of HP steam generated in a boiler**

Parameter  $f_{(e,i,p)}^{\min}$  gives the minimum amount of fuel that can be consumed by the boiler at the corresponding piecewise segment,  $f_{(e,i)}^{\max}$  gives the maximum amount of fuel that can be consumed by the boiler and  $q_{(e,i,p)}^{\min}$  represent the minimum amount of HP steam that can be generated by consuming types of fuel in the boiler at the corresponding piecewise segment. In addition,  $\rho_{(e,i,p)}^{FUEL}$  stand for the gradient coefficient for each piecewise segment per fuel and boiler.

The fuel consumption and the amount of HP steam generated in the boiler is modelled through piecewise linear approximation model according to constraints (3-24) and (3-25). Binary variable  $A_{(e,i,p,t)}$  represents the selection of piecewise segment for each fuel and boiler. Variable  $FT_{(e,i',i,t)}$  represents the fuel consumption in the boiler that is related to the minimum fuel consumption at the

corresponding piecewise segment and the amount of HP steam that can be generated by the boiler ( $QE_{(e,i,t)}$ ).

$$\sum_{i \in \Pi_e} FT_{(e,i',i,t)} \leq f_{(e,i,p)}^{\min} + \rho_{(e,i,p)}^{FUEL} (QE_{(e,i,t)} - qp_{(e,i,p)}^{\min}) + f_{(e,i)}^{\max} (1 - A_{(e,i,p,t)}) \quad \forall e \in E^{FUEL}, i \in I^{BL}, p \in P, t \in T \quad (3-24)$$

$$\sum_{i \in \Pi_e} FT_{(e,i',i,t)} \geq f_{(e,i,p)}^{\min} + \rho_{(e,i,p)}^{FUEL} (QE_{(e,i,t)} - qp_{(e,i,p)}^{\min}) - f_{(e,i)}^{\max} (1 - A_{(e,i,p,t)}) \quad \forall e \in E^{FUEL}, i \in I^{BL}, p \in P, t \in T \quad (3-25)$$

Constraints (3-26) relate two binary variables to determine only a piecewise segment can be chosen for the boiler under operation at each time period.

$$\sum_{p \in P} A_{(e,i,p,t)} = XE_{(e,i,t)} \quad \forall e \in E^{FUEL}, i \in I^{BL}, t \in T \quad (3-26)$$

If a boiler operates, its operating level should be between its minimum and maximum amount of HP steam generated by the boiler for the corresponding piecewise segment. The maximum amount of HP steam generated by the boiler during online cleaning periods is modelled by:

$$\sum_{p \in P} qp_{(e,i,p)}^{\min} A_{(e,i,p,t)} \leq QE_{(e,i,t)} \leq \sum_{p \in P} qp_{(e,i,p)}^{\max} A_{(e,i,p,t)} - \pi_i^{on} V_{(i,t)} \quad \forall e \in E^{FUEL}, i \in I^{BL}, t \in T \quad (3-27)$$

Notice that parameter  $\pi_i^{on}$  is activated only if there is an online cleaning task for a boiler.

### 3.5.2.3.2 Emission constraints

The quantity of emissions for greenhouse gas and SO<sub>x</sub> is modelled according to:

$$QE_{(e,i,t)} = \sum_{e' \in (E^{FUEL} \cap \Pi_e)} \alpha_{(e',e)}^{EMIS} (FT_{(e',i',i,t)} + FS_{(e',i,t)}) \quad \forall e \in E^{EMIS}, i \in I^{BL}, t \in T \quad (3-28)$$

### 3.5.2.3.3 Electricity and steam return constraints

The amount of MP steam and electricity needed by the feed water pump to heat the water and inject the boiling feed water into the boiler are modelled respectively, as given by:

$$RET_{(i,t)} = \alpha_i^{MP} \sum_{e \in E^{HP}} QE_{(e,i,t)} \quad \forall i \in I^{BL}, t \in T \quad (3-29)$$

$$BEL_{(i,t)} = \alpha_i^{EL} \sum_{e \in E^{HP}} QE_{(e,i,t)} \quad \forall i \in I^{BL}, t \in T \quad (3-30)$$

### 3.5.2.4 Operational Constraints for Turbines

In this study, three-stage back pressure steam turbines are used for generation of electricity and several types of steam such as HP, MP and LP steam. The HP steam enters the first stage of the turbine to expand and leaves as MP steam. This MP steam then goes to the second stage of turbine and leaves as LP steam. Finally, the LP steam enters the third stage of the turbine and leaves as an exhaust steam at very low pressure. This exhaust steam is above saturated steam pressure and cannot be used to satisfy production requirement of the production units. After each stage, MP steam and LP steam can be extracted from the turbine to meet steam requirement of the production units. The demand for MP and LP steam can also be satisfied by expanding the steam through pressure relief valves. The material resources balance for each turbine is given by:

$$HP_{(i,t)} = MP_{(i,t)} + LP_{(i,t)} + EP_{(i,t)} \quad \forall i \in I^{TB}, t \in T \quad (3-31)$$

The quantity of exhaust steam that can exit the turbine is given according to:

$$EP_{(i,t)} \geq \alpha_i^{EHST} HP_{(i,t)} \quad \forall i \in I^{TB}, t \in T \quad (3-32)$$

The maximum and minimum amounts of HP steam that can enter turbine are considered by:

$$\beta_i^{\min} \leq HP_{(i,t)} \leq \beta_i^{\max} \quad \forall i \in I^{TB}, t \in T \quad (3-33)$$

The generation of electricity by the turbine are modelled according to:

$$EL_{(i,t)} = \eta_i^{TB} (HP_{(i,t)}(h_b - h_m) + (HP_{(i,t)} - MP_{(i,t)})(h_m - h_l) + (HP_{(i,t)} - MP_{(i,t)} - LP_{(i,t)})(h_l - h_e)) \quad \forall i \in I^{TB}, t \in T \quad (3-34)$$

The major assumption to model the turbine energy balances are: (i) the kinetic and potential energy are negligible in the turbine; (ii) turbine operates

adiabatically; (iii) the steam pressure and temperature at each stage of the turbine are known; and (iv) the turbine efficiency remains constant.

### 3.5.2.4.1 Material resources balance for mixer

The material balance for HP, MP and LP steam are modelled as given by constraint (3-35), (3-36) and (3-37), respectively. The demand for steams should be satisfied for every time period.

$$\sum_{e \in E^{HP}} \sum_{i \in I^{BL}} QB_{(e,i,t)} - HPM_t - \sum_{i \in I^{TB}} HP_{(e,i)} \geq \sum_{e \in E^{HP}} DEM_{(e,t)}^{UT} \quad \forall t \in T \quad (3-35)$$

$$HPM_t + \sum_{i \in I^{TB}} MP_{(i,t)} - MPM_t - \sum_{i \in I^{BL}} RET \geq \sum_{e \in E^{MP}} DEM_{(e,t)}^{UT} \quad \forall t \in T \quad (3-36)$$

$$MPM_t + \sum_{i \in I^{TB}} LP_{(i,t)} \geq \sum_{e \in E^{LP}} DEM_{(e,t)}^{UT} \quad \forall t \in T \quad (3-37)$$

The electricity demand by the production units should be satisfied by the generation of electricity onsite and the purchase of electricity from external source, according to:

$$\sum_{i \in I^{TB}} EL_{(i,t)} \geq \sum_{e \in E^{LL}} DEM_{(e,t)}^{UT} + \sum_{i \in I^{BL}} BEL_{(i,t)} \quad \forall t \in T \quad (3-38)$$

### 3.5.2.5 Demands for Utility Resources (Link between Utility and Production System)

The requirements for utility resources give the linking constraints between utility and production systems. For each time period, the demand for utility resource consists of: (i) fixed utility resource requirements that depend on the operational status of the production unit in the respective task ( $\bar{\alpha}_{(j,i,e)}$ ); and (ii) variable utility resource requirements that depend on the batch size of production unit in the respective processing task ( $\alpha_{(j,i,e)}$ ).

$$\sum_{i \in I_j} \sum_{j \in J_i} \sum_{t'=(t-\tau_{ij}+1)} (\alpha_{(j,i,e)} BT_{(j,i,t')} + \bar{\alpha}_{(j,i,e)} X_{(i,j,t)}^P) = NS_{(e,t)}^{UT} + DEM_{(e,t)}^{UT} \quad \forall e \in E^{UT}, t \in T \quad (3-39)$$

Variable  $NS_{(e,t)}^{UT}$  represent the amount of unsatisfied demand for each utility per time period. This unsatisfied demand for utilities should be acquired from external

sources. A very high purchase cost for utilities is used in the optimisation goal in order to avoid utilities purchases. All the demand for utility resources should be fully satisfied by the internal generation of CHP-based utility system.

### 3.5.2.6 Additional Model: Condition-Based Cleaning Tasks

In this study, condition-based cleaning policies are considered for the boilers of CHP-based utility system. In industrial case study, the model for condition-based cleaning policies can be introduced to any operating unit of production and utility system that require maintenance to avoid potential damage and energy inefficiency of a unit. A more detailed description of additional model on condition-based cleanings policies can be found in Chapter 2. The online and offline cleaning tasks are considered for the condition-based cleaning tasks. The following binary variables are defined to model condition-based cleaning tasks:

$$H_{(i,q,t)} = \begin{cases} 1 & \text{if a cleaning task option } q \text{ for } i \in CB_i^{off} \text{ begins at the start of time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$W_{(i,t)} = \begin{cases} 1 & \text{if an offline cleaning task for } i \in CB_i^{off} \text{ begins at the start of time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$V_{(i,t)} = \begin{cases} 1 & \text{if an online cleaning task for } i \in CB_i^{on} \text{ takes place in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

#### 3.5.2.6.1 Condition-based online cleaning tasks

In any given time period, a boiler could be under online cleaning only if the boiler is under operation during this period, as modelled by:

$$V_{(i,t)} \leq \sum_{e \in E^{FUEL}} XE_{(e,i,t)} \quad \forall i \in CB_i^{on}, t \in T \quad (3-40)$$

A boiler can undergo an online cleaning task after a minimum time period has passed from the occurrence of the previous online cleaning task, as given by:

$$\begin{aligned} \sum_{t'=\max\{1,t-\gamma_i^{on}+1\}}^t V_{(i,t')} &\leq 1 & \forall i \in CB_i^{on}, t \in T \\ V_{(i,t)} &= 0 & \forall i \in CB_i^{on}, t \leq (\gamma_i^{on} - \tilde{\gamma}_i^{on}) : \tilde{\gamma}_i^{on} < \gamma_i^{on} \end{aligned} \quad (3-41)$$

Parameters  $\tilde{\gamma}_i^{on}$  and  $\gamma_i^{on}$  represent the total number of time periods that has passed since the last online cleaning at the beginning of the planning horizon and the minimum time between two consecutive online cleaning tasks in a boiler, respectively.

### 3.5.2.6.2 Condition-based cleaning tasks: unit performance degradation and recovery

The performance of boilers in CHP-based utility system that is subject to condition-based cleaning is modelled through the extra energy consumption  $U_{(i,t)}$  due to its deviation from its completely clean condition. It is assumed that the performance of a boiler decreases as this extra energy consumption increases. This extra energy consumption for the boiler under operation should not exceed a maximum extra energy consumption limit  $v_i^{\max}$ , as defined by:

$$U_{(i,t)} \leq v_i^{\max} \sum_{e \in E^{FUEL}} XE_{(e,i,t)} \quad \forall i \in CB_i, t \in T \quad (3-42)$$

The extra energy consumption of an operating boiler is related to its cumulative time of operation  $R_{(i,t)}$  and its cumulative operating level deviation  $D_{(i,t)}$ , through parameters  $\delta_i$  and  $\delta_i^{cd}$  that represent the corresponding degradation rates, as given by:

$$\begin{aligned} U_{(i,t)} &\geq \delta_i R_{(i,t)} + \delta_i^{cd} D_{(i,t)} - v_i^{\max} \left(1 - \sum_{e \in E^{FUEL}} XE_{(e,i,t)}\right) & \forall i \in CB_i, t \in T \\ U_{(i,t)} &\leq \delta_i R_{(i,t)} + \delta_i^{cd} D_{(i,t)} + v_i^{\max} \left(1 - \sum_{e \in E^{FUEL}} XE_{(e,i,t)}\right) & \forall i \in CB_i, t \in T \end{aligned} \quad (3-43)$$

### 3.5.2.6.3 Cumulative time of operation

The occurrence of an offline cleaning task in a boiler resets its cumulative time of operation to zero, according to:



$$R_{(i,t)} \leq \bar{\mu}_{(i,t)}(1 - W_{(i,t)}) \quad \forall i \in CB_i^{off}, \forall t \in T \quad (3-44)$$

Parameters  $\bar{\mu}_{(i,t)}$  are sufficiently large numbers. The cumulative time of operation for a boiler subject to condition-based cleaning is modelled by the following set of constraints:

$$\begin{aligned} R_{(i,t)} &\leq (\tilde{\rho}_i + \sum_{e \in E^{FUEL}} XE_{(e,i,t)}) + \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, t \in T : t = 1 \\ R_{(i,t)} &\leq (R_{(i,t-1)} + \sum_{e \in E^{FUEL}} XE_{(e,i,t)}) + \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, t \in T : t > 1 \end{aligned} \quad (3-45)$$

$$\begin{aligned} R_{(i,t)} &\geq (\tilde{\rho}_i + \sum_{e \in E^{FUEL}} XE_{(e,i,t)}) - \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, \forall t \in T : t = 1 \\ R_{(i,t)} &\geq (R_{(i,t-1)} + \sum_{e \in E^{FUEL}} XE_{(e,i,t)}) - \bar{\mu}_{(i,t)}(W_{(i,t)} + V_{(i,t)}) & \forall i \in CB_i, \forall t \in T : t > 1 \end{aligned} \quad (3-46)$$

$$\begin{aligned} R_{(i,t)} &\geq (\tilde{\rho}_i + 1)(1 - \rho_i^{rec}) - \bar{\mu}_{(i,t)}(1 - V_{(i,t)}) & \forall i \in CB_i^{on}, \forall t \in T : t = 1 \\ R_{(i,t)} &\geq (R_{(i,t-1)} + 1)(1 - \rho_i^{rec}) - \bar{\mu}_{(i,t)}(1 - V_{(i,t)}) & \forall i \in CB_i^{on}, \forall t \in T : t > 1 \end{aligned} \quad (3-47)$$

For every boiler, parameter  $\rho_i^{rec}$  represents the corresponding performance recovery factor due to its online cleaning and parameter  $\tilde{\rho}_i$  denotes the cumulative time of operation just before the beginning of the planning horizon of interest (i.e., initial state).

#### 3.5.2.6.4 Cumulative operating level deviation

The constraints that describe the cumulative operating level deviation for boilers subject to condition-based cleaning are presented. The occurrence of an offline cleaning task in a boiler resets its cumulative operating level deviation to zero, as defined by:

$$D_{(i,t)} \leq \mu_{(i,t)}(1 - W_{(i,t)}) \quad \forall i \in CB_i^{off}, t \in T \quad (3-48)$$

Parameters  $\mu_{(i,t)}$  are sufficiently large numbers. The cumulative operating level deviation of a boiler in CHP-based utility system resets to zero only after the occurrence of an offline cleaning task.

The new sets of constraints for the modelling of the cumulative operating level deviation of the boilers subject to condition-based cleaning are presented below:

$$\begin{aligned}\bar{Q}_{(i,t)}^{dev} &\leq \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) + \mu_{(i,t)} \left( 1 - \sum_{e \in E^{FUEL}} XE_{(e,i,t)} \right) \quad \forall i \in (CB_i \cap I^{BL}), t \in T \\ \bar{Q}_{(i,t)}^{dev} &\geq \left( \frac{|q_{(i,t)}^{ref} - QS_{(i,t)}|}{q_{(i,t)}^{ref}} \right) - \mu_{(i,t)} \left( 1 - \sum_{e \in E^{FUEL}} XE_{(e,i,t)} \right) \quad \forall i \in (CB_i \cap I^{BL}), t \in T \\ \bar{Q}_{(i,t)}^{dev} &\leq \mu_{(i,t)} \sum_{e \in E^{FUEL}} XE_{(e,i,t)} \quad \forall i \in (CB_i \cap I^{BL}_i), t \in T\end{aligned}\tag{3-49}$$

$$\begin{aligned}D_{(i,t)} &\leq \tilde{\rho}_i^{cd} + \bar{Q}_{(i,t)}^{dev} + \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall i \in (CB_i \cap I^{BL}), t \in T : t = 1 \\ D_{(i,t)} &\leq D_{(i,t-1)} + \bar{Q}_{(i,t)}^{dev} + \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall i \in (CB_i \cap I^{BL}), t \in T : t > 1\end{aligned}\tag{3-50}$$

$$\begin{aligned}D_{(i,t)} &\geq \tilde{\rho}_i^{cd} + \bar{Q}_{(i,t)}^{dev} - \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall i \in (CB_i \cap I^{BL}), t \in T : t = 1 \\ D_{(i,t)} &\geq D_{(n,i,t-1)} + \bar{Q}_{(i,t)}^{dev} - \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall i \in (CB_i \cap I^{BL}), t \in T : t > 1\end{aligned}\tag{3-51}$$

$$\begin{aligned}D_{(i,t)} &\geq (\tilde{\rho}_i^{cd} + \bar{Q}_{(i,t)}^{dev})(1 - \rho_i^{rec}) - \mu_{(i,t)} (1 - V_{(i,t)}) \quad \forall i \in (CB_i^{on} \cap I^{BL}), t \in T : t = 1 \\ D_{(i,t)} &\geq (D_{(i,t-1)} + \bar{Q}_{(i,t)}^{dev})(1 - \rho_i^{rec}) - \mu_{(i,t)} (1 - V_{(i,t)}) \quad \forall i \in (CB_i^{on} \cap I^{BL}), t \in T : t > 1\end{aligned}\tag{3-52}$$

New variables  $\bar{Q}_{(i,t)}^{dev}$  have been defined to describe the additional cumulative operating level deviation from a reference operating level  $q_{(i,t)}^{ref}$ . The cumulative operating level deviation becomes zero if and only if a boiler undergoes an offline cleaning. For every unit, parameter  $\tilde{\rho}_i^{cd}$  represents its cumulative operating level deviation just before the beginning of the planning horizon of interest (i.e., initial state). The reference operating level of a boiler  $qb_i^{ref}$  is assumed to be the maximum operating capacity  $\beta_i$ .

### 3.5.2.6.5 Operational constraints for offline cleaning tasks

The following set of constraints ensure that a unit that is under offline cleaning remains closed for the whole duration of the selected offline cleaning task option, and relate the two binary variables for offline cleaning tasks.

$$\sum_{e \in E^{FUEL}} XE_{(e,i,t)} + \sum_{t'=\max\{\tau_i^{es}, t-v_{(i,q)}+1\}}^{\min\{\tau_i^{ls}, t\}} H_{(i,q,t')} \leq 1 \quad \forall i \in (FM_i \cup CB_i^{off}), q \in Q_i, \tau_i^{es} \leq t \leq (\tau_i^{ls} + v_{(i,q)} - 1) \quad (3-53)$$

$$W_{(i,t)} = \sum_{q \in Q_i} H_{(i,q,t)} \quad \forall i \in (FM_i \cup CB_i^{off}), t \in T : \tau_i^{es} \leq t \leq \tau_i^{ls} \quad (3-54)$$

For condition-based offline cleaning tasks, earliest and latest starting times should be set equal to the first and the last period of the planning horizon, respectively.

### 3.5.2.6.6 Resource constraints for cleaning tasks

In the same line with the previous chapter (i.e., Chapter 2), a limited amount of available resources for cleaning operations shared by all types of cleaning tasks is considered, according to:

$$\sum_{i \in CB_i^{on}} g_i^{on} V_{(i,t)} + \sum_{i \in CB_i^{off}} \sum_{q \in Q_i} \sum_{t'=\max\{\tau_i^{es}, t-v_{(i,q)}+1\}}^t g_{(i,q)}^{off} H_{(i,q,t')} + \sum_{i \in FM_i} \sum_{q \in Q_i} \sum_{t'=\max\{\tau_i^{es}, t-v_{(i,q)}+1\}}^{\min\{\tau_i^{ls}, t\}} g_{(i,q)}^{off} H_{(i,q,t')} \leq \eta_t^{\max} - \sum_{i \in DM_i} \tilde{\eta}_{(i,t)} \quad \forall t \in T \quad (3-55)$$

For every unit, parameters  $g_i^{on}$  and  $g_{(i,q)}^{off}$  denote the resource requirements for online cleaning and different offline cleaning task options, respectively.

### 3.5.2.6.7 Terminal constraint

The terminal constraint is applied for the last time period  $|T|$  and related to desired unit performance level, according to:

$$U_{(i,t)} \leq \lambda_i^U v_i^{\max} \quad \forall i \in CB_i, t \in T : t = |T| \quad (3-56)$$

## 3.5.3 Objective Functions

There are two optimisation goals that need to be achieved in this study: (i) makespan minimization; and (ii) total cost minimization. The purpose to minimise makespan of the integrated optimisation model is to find the optimal cumulative time periods to produce final products and order delivery. Furthermore, the optimal cumulative time periods obtained as the results of makespan

minimization is used as the total planning horizon to further optimise the integrated model for cost minimization without performance degradation and recovery model.

$$\min \left[ MS \geq \sum_t tG_{(e,i,t)} + \sum_{t \in T} \sum_{e \in E^{UT}} \phi_{(e,t)}^{UT,ex} NS_{(e,t)}^{UT} \right] \quad \forall e \in E^{PR}, i \in CS_i \quad (3-57)$$

The makespan minimization includes cost for purchasing utilities. A very high purchase cost coefficient for utilities are introduced in order to avoid purchases of utilities and to fully utilise the internal utilities generation from the CHP-based utility system.

$$\min \left[ \begin{aligned} & \sum_{t \in T} \sum_{e \in E^{FUEL} \cup E^{HP}} \sum_{i \in I^{SF}} (\phi_{(i,t)}^S SE_{(e,i,t)} + \phi_{(i,t)}^F FE_{(e,i,t)}) \\ & + \sum_{t \in T} \sum_{e \in E^{FUEL}} \sum_{i \in IT_e} \sum_{i' \in I^{BL}} (\phi_e^{FUEL} (FT_{(e,i,i',t)} + FS_{(e,i',t)})) \\ & + \sum_{t \in T} \sum_{e \in E^{FUEL}} \sum_{i \in I^{BL}} (\phi_{(i,t)}^{BL,fix} XE_{(e,i,t)} + \phi_{(i,t)}^{BL,var} QE_{(e,i,t)}) \\ & + \sum_{t \in T} \sum_{e \in E^{HP}} \sum_{i \in I^{TB}} (\phi_{(i,t)}^{TB,fix} XE_{(e,i,t)} + \phi_{(i,t)}^{TB,var} HP_{(i,t)}) \\ & + \sum_{t \in T} \sum_{e \in E^{EMIS}} \sum_{i \in I^{BL}} \phi_e^{EMIS} QE_{(e,i,t)} \\ & + \sum_{t \in T} \sum_{e \in E^{UT}} \phi_{(e,t)}^{UT,ex} NS_{(e,t)}^{UT} \\ & + \sum_{t \in T} \sum_{j \in J_i} \sum_{i \in PR_i} (\phi_{(i,t)}^{PR,var} B_{(j,i,t)} + \phi_{(i,t)}^{PR,fix} XP_{(j,i,t)}) \\ & + \sum_{t \in T} \sum_{e \in IT_e} \sum_{i \in ZI_i} \phi_{(e,i)}^{STOR} XZ_{(e,i,t)} \\ & + \sum_{t \in T} \left( \sum_{i \in CB_i^{on}} \phi_{(i,t)}^{on} V_{(i,t)} + \sum_{i \in CB_i^{off} \cup FM_i} \sum_{q \in Q_i} \phi_{(i,q,t)}^{off} H_{(i,q,t)} \right) \\ & + \sum_{t \in T} \sum_{i \in CB_i} \phi_{(i,t)}^{pw} U_{(i,t)} \end{aligned} \right] \quad (3-58)$$

The cost minimization consists of: (i) the startup and shutdown costs for units under startup and shutdown action; (ii) the fuel costs; (iii) the fixed and variable costs for boilers; (iv) the fixed and variable costs for turbines in CHP system; (v) the emissions costs; (vi) the purchase costs for acquiring electricity and other utility resources from external sources; (vii) the variable and fixed operational costs for production units; (viii) storage costs for inventory tanks of product

resources; (ix) online and offline cleaning costs for units under condition-based cleaning; and (x) total extra energy consumption costs for units that are subject to performance degradation model.

### 3.5.4 Model Decomposition Strategy

Figure 3-2 displays a schematic representation of the steps of the proposed three-stage decomposition strategy. In the first stage of decomposition strategy, the planning problem of production system is solved by defining the upper bound on total utility generation per time period. The right hand side of constraints (3-39) is replaced with the maximum total utility generation. The total utility generation can be calculated by multiplying maximum capacity of a unit with the coefficient of utility resource requirements. The constraints that are included in the planning problem of multistage production system are constraints (3-1) to (3-14). Once the planning of production system is derived, the utility needs of each production unit are known. The utility generation target from the production of product resources (i.e.,  $B_{(e,i,t)}$ ,  $BT_{(i,j,t)}$ ,  $FT_{(e,i,i',t)}$ ) and operational status of production units (i.e.,  $XP_{(i,j,t)}$ ,  $XZ_{(e,i,t)}$ ,  $X_{(i,t)}$ ,  $WT_{(e,i,i',t)}$ , and  $G_{(e,i,t)}$ ) are fixed before solving the planning problem of utility system in the second stage of decomposition strategy. The constraints that are included in the planning problem of CHP-based utility system are constraints (3-15) to (3-56). It needs to be highlighted that the first and second stage of decomposition strategy is the traditional sequential approach. Finally, in the third stage of the decomposition strategy, the operational status (i.e.,  $XE_{(e,i,t)}$ ,  $SE_{(e,i,t)}$ ,  $FE_{(e,i,t)}$ ) of utility units is fixed with the exclusion of the time period when purchase of utilities occurs. The overall integrated planning of production and utility system is optimised simultaneously to obtain the final solutions.

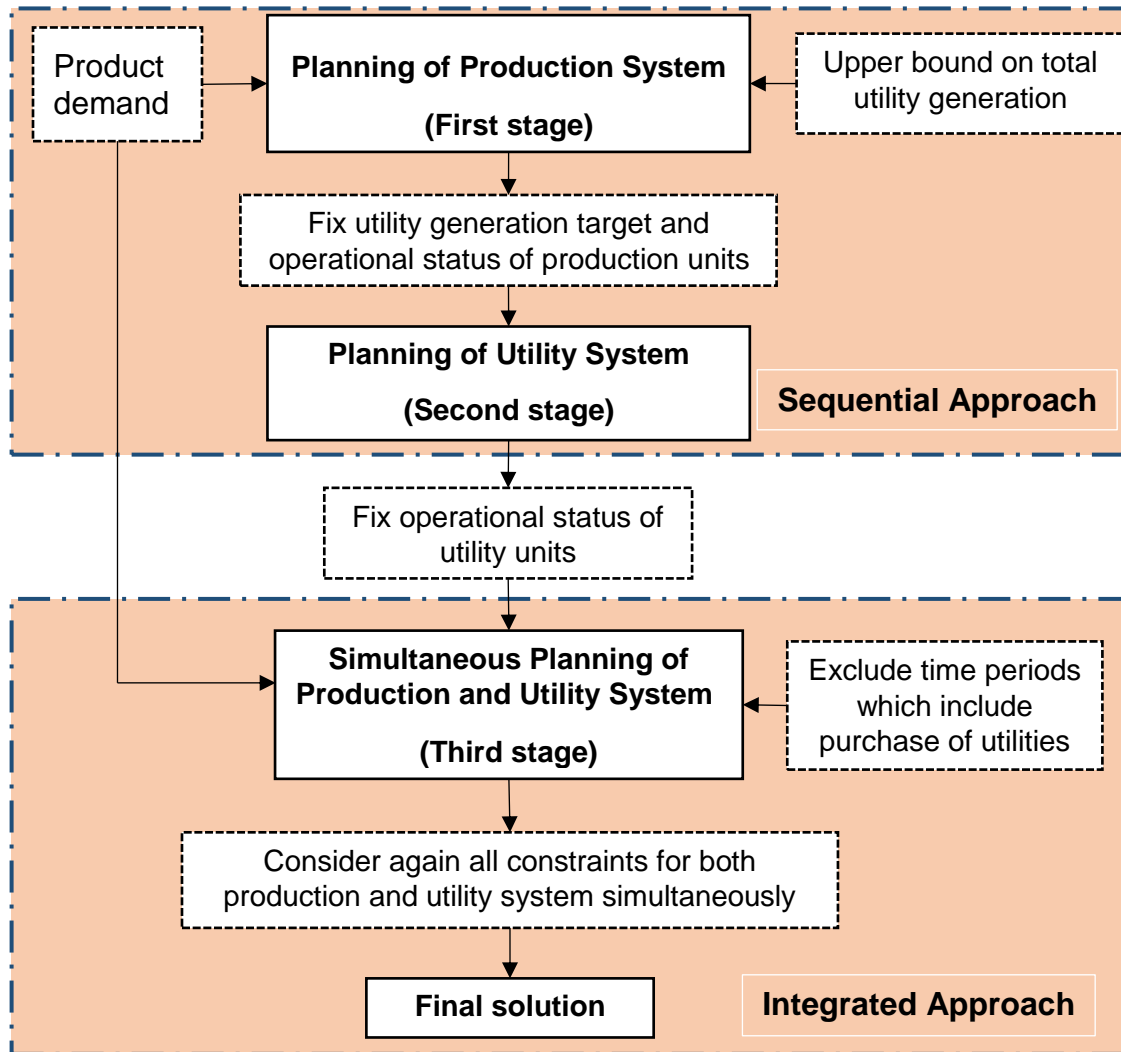


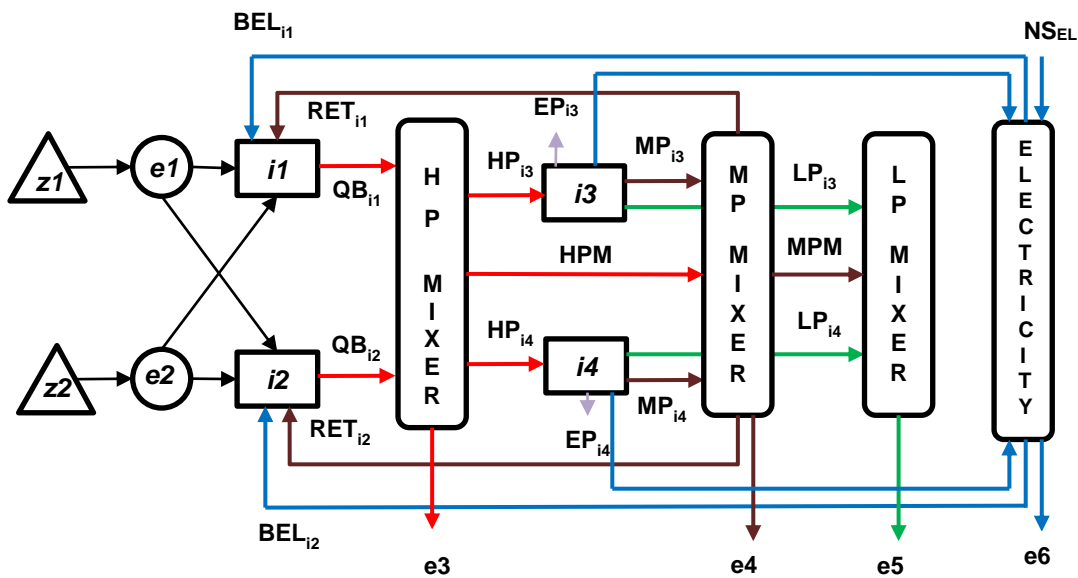
Figure 3-2 Planning method via three-stage decomposition strategy

### 3.6 Multistage Production System and Combined Heat and Power Utility System

#### 3.6.1 Description of Production and Utility System

The integrated system under consideration consists of multistage production network and combined heat and power utility system. Figure 3-3 displays representative layout of CHP-based utility system in a typical industrial plant. The CHP system consists of two boilers  $i1$  and  $i2$  that can burn two types of fuels  $e1$  and  $e2$  to generate HP steam (i.e.,  $e3$ ). The fuels are stored in their associated inventory tanks  $z1$  and  $z2$ , respectively. The emissions that are released from

the combustion processes in the boilers are sulphur oxide (SO<sub>x</sub>) (i.e., *e17*) and carbon dioxide (CO<sub>2</sub>) (i.e., *e18*). The boilers also require MP steam (i.e., *e4*) and electricity (i.e., *e6*) that are generated by two steam turbines *i3* and *i4*. The steam turbines utilise HP steam to cogenerate electricity and several types of steams (i.e., MP steam, LP steam, and exhaust steam). The MP (i.e., *e4*) and LP (i.e., *e5*) steam can also be expanded through pressure relief valves to satisfy steam demands. The exhaust steam is released to the environment because it is a very low pressure steam that does not meet standard process requirement of the production system.



**Figure 3-3 Combined Heat and Power Utility System (Agha et al., 2010)**

Figure 3-4 shows the representative layout of multistage production system with different batching restriction for product resources. The production system can produce six intermediate product resources (*e9-e11, e13, e14*) and two final product resources (*e15* and *e16*) which could be stored in their associated inventory tanks (*z6-z9*). The production network consists of six tasks (*T1-T6*) and for each task, there are associated production units (*i5-i9*). The batches of product resources *e10*, *e11*, and *e13* are not allowed to be mixed or split, the batch of product resource *e9* is not allowed to be mixed and the batch of product resource *e16* is not allowed to be split. The tasks *T1*, *T2* and *T5* can consume

raw material resources  $e7$ ,  $e8$  and  $e12$ , respectively. Task  $T3$  and  $T6$  both can consume two intermediate product resources with different batching restrictions. Meanwhile, task  $T4$  can produce intermediate product resource  $e14$  and final product resource  $e15$ . There are two customers  $C1$  and  $C2$  that require final product resources  $e15$  and  $e16$ , respectively. The production units in each task may need several types of utility resources as highlighted in coloured arrows in Figure 3-4.

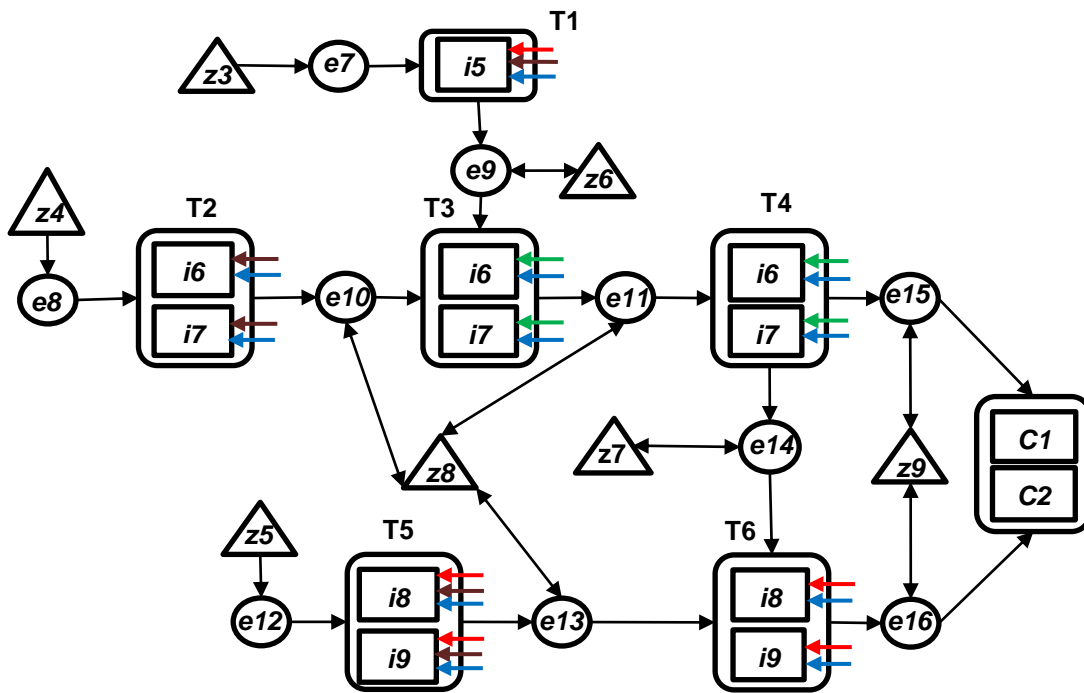


Figure 3-4 Multistage production network with batching restrictions (Velez and Maravelias, 2013)



**Table 3-1 Operating characteristics for the CHP system**

Fuel	$e1$	$e2$
$\alpha_{(e17,e)}^{EMIS}$	0.013	0.026
$\alpha_{(e18,e)}^{EMIS}$	2.466	1.858
Boiler	$i1$	$i2$
$f_{(e,i)}^{max}$	1000	1000
$f_{(e1,i,p1)}^{min}$	8.152	13.098
$f_{(e1,i,p2)}^{min}$	24.703	38.883
$f_{(e1,i,p3)}^{min}$	40.760	64.157
$f_{(e2,i,p1)}^{min}$	10.033	16.122
$f_{(e2,i,p2)}^{min}$	30.680	48.291
$f_{(e2,i,p3)}^{min}$	51.877	81.655
$\rho_{(e1,i,p1)}$	0.144	0.198
$\rho_{(e1,i,p2)}$	0.184	0.253
$\rho_{(e1,i,p3)}$	0.459	0.632
$\rho_{(e2,i,p1)}$	0.180	0.247
$\rho_{(e2,i,p2)}$	0.242	0.334
$\rho_{(e2,i,p3)}$	0.766	1.055
$fuel_{(e1,i)}^s$	1.734	3.509
$fuel_{(e2,i)}^s$	2.024	4.093
$\alpha_i^{MP}$	0.1	0.1
$\alpha_i^{EL}$	0.002	0.003
$qb_{(e1,i,p1)}^{min}$	60	70
$qb_{(e1,i,p2)}^{min}$	175	200
$qb_{(e1,i,p3)}^{min}$	262.5	300
$qb_{(e2,i,p1)}^{min}$	60	70
$qb_{(e2,i,p2)}^{min}$	175	200
$qb_{(e2,i,p3)}^{min}$	262.5	300
$qb_{(e1,i,p1)}^{max}$	175	200
$qb_{(e1,i,p2)}^{max}$	262	300
$qb_{(e1,i,p3)}^{max}$	350	400
$qb_{(e2,i,p1)}^{max}$	175	200
$qb_{(e2,i,p2)}^{max}$	262	300
$qb_{(e2,i,p3)}^{max}$	350	400
Turbine	$i3$	$i4$
$h_m$	2.955	2.955
$h_l$	2.838	2.838
$h_e$	2.752	2.752

**Table 3-2 Minimum and maximum operating capacities for production and utility units**

Unit	$i1$	$i2$	$i3$	$i4$	$i5$	$i6$	$i7$	$i8$	$i9$
$\beta_i^{min}$	60	70	100	100	5	20	45	10	20
$\beta_i^{max}$	350	400	500	500	10	75	50	40	40

**Table 3-3 Fixed and varied stoichiometric coefficients of utility needs for production units (per unit of task)**

Unit	Task	$\alpha_{(j,i,e3)}$	$\alpha_{(j,i,e4)}$	$\alpha_{(j,i,e5)}$	$\alpha_{(j,i,e6)}$	$\bar{\alpha}_{(j,i,e3)}$	$\bar{\alpha}_{(j,i,e4)}$	$\bar{\alpha}_{(j,i,e5)}$	$\bar{\alpha}_{(j,i,e6)}$
$i5$	$T1$	3.3	4.5		0.3	11	9		8
$i6$	$T2$		0.7		0.9		6		7
	$T3$			1.1	0.5			9	6
	$T4$			0.5	0.2			11	7
$i7$	$T2$		0.9		0.5		6		7
	$T3$			2.0	0.4			10	9
	$T4$			0.9	0.1			9	8
$i8$	$T5$	3.3	0.8		0.2	6	5		7
	$T6$	3.3			3.2	7			9
$i9$	$T5$	2.3	1.1		0.4	7	4		5
	$T6$	2.3			2.2	15			12

**Table 3-4 Maximum inventory levels for inventory tanks of fuels and product resources**

Inventory tanks	$z1$	$z2$	$z3$	$z4$	$z5$	$z6$	$z7$	$z8$	$z9$
$\varepsilon_i^{max}$	3,000	10,000	500	500	500	150	150	150	150

Table 3-1 shows the operating characteristics for the CHP-based utility system. Each production and utility unit has a minimum and maximum capacity, as given by Table 3-2. Table 3-3 provides the stoichiometric coefficients of fixed and varied utility needs for production units that are processing the associated task. The maximum inventory level for inventory tanks for product resources and fuels is shown in Table 3-4.

**Table 3-5 Processing time and conversion coefficient for each task**

Processing time		Conversion coefficient $\rho_{(e,j)}$													
$\tau_{(i,j)}$															
	<i>i5</i>	<i>i6</i>	<i>i7</i>	<i>i8</i>	<i>i9</i>	<i>e7</i>	<i>e8</i>	<i>e9</i>	<i>e10</i>	<i>e11</i>	<i>e12</i>	<i>e13</i>	<i>e14</i>	<i>e15</i>	<i>e16</i>
<i>T1</i>	1					-1	1								
<i>T2</i>	1	2					-1	1							
<i>T3</i>	2	3						-0.1	-0.9	1					
<i>T4</i>	3	1								-1			0.4	0.6	
<i>T5</i>			2	4							-1	1			
<i>T6</i>			3	1									-0.5	-0.5	1

**Table 3-6 Operational costs for utility and production units**

unit	task	$\phi_{(i,t)}^S$	$\phi_{(i,t)}^F$	$\phi_{(i1-i2,t)}^{fix} / \phi_{(j,i5-i9)}^{fix}$	$\phi_{(i1-i2,t)}^{var} / \phi_{(j,i5-i9)}^{var}$
<i>i1</i>	-	2,250	1,150	4	2
<i>i2</i>	-	2,270	1,200	4	2
<i>i3</i>	-	1000	900	3	1
<i>i4</i>	-	1000	900	3	1
<i>i5</i>	<i>T1</i>	-	-	12	8
<i>i6</i>	<i>T2   T3   T4</i>	-	-	4   8   4	16   12   16
<i>i7</i>	<i>T2   T3   T4</i>	-	-	8   12   12	12   8   8
<i>i8</i>	<i>T5   T6</i>	-	-	8   12	12   8
<i>i9</i>	<i>T5   T6</i>	-	-	16   4	4   16

The fixed processing time in a unit and conversion coefficient of product resources for each task is given by Table 3-5. The operational costs for utility and product resources are given in Table 3-6. Note that, information related to production units is obtained from Velez and Maravelias (2013) and information for utility units is taken from Agha et al. (2010). The emission costs for SO<sub>x</sub> is 23 monetary units (m.u.)/ton and no emission costs for greenhouse gases is considered. The fuel costs for the use of fuel *e1* and *e2* in the boilers are 30 m.u./ton and 18 m.u./ton, respectively. Purchase costs for utility resources (i.e., *e3* - *e6*) are 6000 m.u./unit. Table 3-7 provides the additional operational

parameters for boilers and turbines in CHP-based utility system. The parameters that refer to condition-based offline and online cleaning are defined in Table 3-8.

**Table 3-7 Additional parameters for boilers and turbines in CHP-based utility system**

Symbol	Value	Unit	Description
$\omega_i$	5	hours	Minimum runtime for boilers and turbines
$\psi_i$	2	hours	Minimum shutdown time for boilers and turbines
$o_{i3}$	12	hours	Maximum runtime for turbines $i3$
$o_{i4}$	14	hours	Maximum runtime for turbines $i4$
$\eta_i^{max}$	12	Resource unit	Available cleaning resources per time period

**Table 3-8 Parameters related to the condition-based cleaning of boilers in CHP-based utility system**

Parameters	$i1$	$i2$	Description
$V_i^{max}$	100	84	Extra energy consumption limit
$\delta_i$	5	6	Performance degradation rate
$\delta_i^{cd}$	6.75	6.75	Performance related to operating level
$\gamma_i^{on}$	14	14	Minimum time between two online cleanings
$\rho_i^{rec}$	0.2	0.2	Performance recovery factor
$q_{(i,t)}^{ref}$	350	400	Reference operating level
$v_i^{on}$	1	1	Necessary cleaning resources for online cleaning
$\lambda_i^U$	0.75	0.75	Percentage coefficient for maximum extra energy consumption at the end of time period
$\pi_i^{on}$	0.2	0.2	Percentage modification on maximum amount of HP steam of boiler that is under online cleaning

There are three alternative condition-based cleaning options as shown in Table 3-9. In addition, the parameters that define the initial states of the system are given in Table 3-10. The initial inventory for fuels  $e1$  and  $e2$  is 3000 tons, respectively and initial inventory for raw materials  $e7, e8$  and  $e12$  is 500 tons,

respectively. Customer  $C1$  requires 50 kg of final product resources  $e15$  and 60 kg of final product resource  $e16$ . Customer  $C2$  requires 25 kg and 40 kg of final product resources  $e15$  and  $e16$ , respectively.

**Table 3-9 Alternative options for condition-based offline cleaning tasks**

units	parameter	metric unit	$q1$	$q2$	$q3$
$i1$	$\nu_{(i,q)}$	hours	1	2	3
$i2$	$\vartheta_{(i,q)}^{off}$	resource units	6	4	3
$i1, i2$	$\phi_{(i,q,t)}^{off}$	m.u./cleaning	300	200	150

**Table 3-10 Initial state of boilers and turbines in CHP-based utility system**

Parameter	$i1$	$i2$	$i3$	$i4$
$\tilde{\chi}_{(e,i)}$	$e2$	$e1$	$e3$	$e3$
$\tilde{\rho}_i$	10	10	-	-
$\tilde{\gamma}_i^{on}$	6	7	-	-
$\tilde{\omega}_i$	-	-	10	10
$\tilde{\psi}_i$	0	0	0	0
$\tilde{\rho}_i^{cd}$	2	1	-	-

### 3.6.2 Computational Experiments

In this section, the descriptions of problem instances are introduced and the results of these computational experiments are presented. The purposes of computational experiments are to compare: (i) the best solution found, (ii) the computational time and optimality gap, and (iii) the purchases of utilities from external sources between integrated approach, sequential approach and the proposed decomposition strategy.

#### 3.6.2.1 Description of Computational Experiments

In this study, 16 different problem instances have been solved for integrated approach, sequential approach and the proposed decomposition strategy as shown in Table 3-11. For every problem instance, the optimisation model differs

in: (i) optimisation goal (i.e., makespan or total costs), (ii) number of total planning horizon, (iii) changes in the magnitude of certain parameters (i.e., product demand,  $\zeta_{(e,i)}$  or varied stoichiometric coefficient of utility needs,  $\alpha_{(j,i,e)}$ ), (iv) with/without considering performance degradation and recovery model, and (v) the units that are subject to startup and shutdown cost ( $I^{SF}$ ), minimum runtime ( $I^{S-\min}$ ), shutdown time ( $I^{F-\min}$ ) and maximum runtime ( $MR_i$ ). The problem instances I.01 to I.10 are solved without considering performance degradation and recovery model. Meanwhile, the problem instances I.11 to I.16 are solved by considering: (i) performance degradation and recovery model for boilers, (ii) startup and shutdown cost ( $I^{SF}$ ), minimum runtime ( $I^{S-\min}$ ) and shutdown time ( $I^{F-\min}$ ) for boilers and turbines, and (iii) maximum runtime ( $MR_i$ ) for turbines.

For the problem instances where the optimisation goal is the minimization of total cost (i.e., I.04 to I.06, I.09, I.10 and I.14), the total planning horizon is the optimum makespan found in the integrated approach (i.e., I.01 to I.03, I.07, I.08 and I.11). In contrast to the problem instances I.15 and I.16, the total planning horizon of these problem instances are taken from the optimum makespan found in decomposition strategy of problem instances I.12 and I.13, respectively. The reasons are: (i) no purchases of utilities are reported in the solution of the proposed decomposition strategy, and (ii) high optimality gap within maximum predefined time limit for the solution of integrated approach in both of the problem instances I.12 and I.13.

The original problem instance for the minimization of makespan and total cost are: (i) the problem instances I.01 and I.04, respectively, and (ii) the problem instances I.11 and I.14, respectively. The following problem instances are set by increasing the magnitude of product demand ( $\zeta_{(e,i)}$ ) for minimization of makespan (i.e., I.02, I.03, I.12 and I.13) and for minimization of total cost (i.e., I.05, I.06, I.15 and I.16). The rest of problem instances are set by increasing the varied stoichiometric coefficient of the utility needs ( $\alpha_{(j,i,e)}$ ) for minimization of makespan (i.e., I.07 and I.08) and minimization of total cost (i.e., I.09 and I.10).

### 3.6.2.2 Results of Computational Experiments

The proposed decomposition strategy has been tested on a total number of 16 problem instances in order to validate its performances in term of best solution, optimality gap and purchases of utilities from external sources. All problem instances have been written in GAMS 24.8 (Brooke, et al., 1998) and solved with the MIP solver CPLEX 12.7 (ILOG, 2017) in an Intel(R) core(TM) i7-6700CPU@ 3.4 GHz with 8 GB RAM under standard configurations.

Table 3-11 shows the comparison between the best solutions found in integrated approach, sequential approach and proposed decomposition strategy within maximum predefined time limit (i.e., 3,600 CPU seconds). Note that, for each corresponding problem instance, the best solution that is found in the integrated or sequential approach is the optimal solution or the worst solution, respectively. Meanwhile, the best solution found in the proposed decomposition strategy can be optimal or near-optimal solution according to the definition of problem instances.

For example, problem instance I.04, I.05 and I.06 show the total cost that is obtained in the proposed decomposition strategy is equal to the integrated approach but lower than that of the sequential approach. In addition, the computational time of decomposition strategy is faster than that of integrated approach by an average magnitude of 4 but slower than that of the sequential approach. No purchases of utilities from external source were reported in the solution of the proposed decomposition strategy and integrated approach. Although the computational time of sequential approach records the fastest CPUs time, there is penalty cost of purchases of utilities. Similar observation is established for problem instances under cost minimization (i.e., I.05, I.06, and I.09).

Other important observation is that the best solution found in the proposed decomposition strategy may achieve near optimal solution in comparison to the optimal solution found in integrated approach. For example, problem instance I.10 shows that the difference in minimum total cost between integrated approach

and decomposition strategy is about 1.7%. Similar observation for problem instances I.14, I.15 and I.16. The reason of obtaining near-optimal solution as found in the proposed decomposition strategy of these problem instances is due to the utility units in the proposed decomposition strategy are operating in more time periods than that of the integrated approach which increase slightly the fuel and operational costs. The proposed decomposition strategy in the third stages finds a solution to avoid purchases of utilities that occurred in the first two stages (i.e., sequential solution). In addition, no purchase of utilities is reported in the solution of decomposition strategy. Meanwhile, the integrated approach finds the potential to further reduce the total costs by performing more cleanings on the units.

In addition, decomposition strategy has been solved to achieve a zero optimality gap. However, integrated approach did not achieve a zero optimality gap within the maximum predefined time limit. These results show that the proposed decomposition strategy can obtain optimal or near-optimal solutions as found in the solutions of integrated approach at further reduced computational time and a zero optimality gap with no penalty cost of purchases of utilities for all problem instances under cost minimization.



**Table 3-11 Comparison of the best solutions found in integrated approach, sequential approach and proposed decomposition strategy within maximum predefined time limit**

Problem instance	Objective	Planning horizon	Parameter	Integrated Approach			Proposed decomposition strategy		Sequential Approach		$NS_{(e,t)}^{UT}$
				Best sol.	Total CPUs	Gap %	Best sol.	Total CPUs	Best sol.	Total CPUs	
I.01	MS	24	$\zeta_{(e,i)}$	10	14	0	10	6	10	2	18.4
I.02	MS	24	1.1 $\zeta_{(e,i)}$	11	1,003	0	11	238	11	19	0
I.03	MS	24	1.2 $\zeta_{(e,i)}$	11	641	0	11	147	11	38	0
I.04	Cost	10	$\zeta_{(e,i)}$	41,102	226	0	41,102	31	594,074	10	90.3
I.05	Cost	11	1.1 $\zeta_{(e,i)}$	45,303	107	0	45,303	68	45,922	16	0
I.06	Cost	11	1.2 $\zeta_{(e,i)}$	48,719	302	0	48,719	76	49,360	26	0
I.07	MS	24	1.5 $\alpha_{(j,i,e)}$	12	3,077	0	10	28	10	15	75.0
I.08	MS	24	1.6 $\alpha_{(j,i,e)}$	14	3,600	27.5	10	64.5	10	3	164.1
I.09	Cost	12	1.5 $\alpha_{(j,i,e)}$	60,536	406	0	60,536	329	1,141,199	32	177.1
I.10	Cost	14	1.6 $\alpha_{(j,i,e)}$	59,390	3,600	9.4	60,427	1,566	915,945	594	138.9
I.11	MS	24	$\zeta_{(e,i)}$	10	1,163	0	10	13.6	10	2.0	25.1
I.12	MS	24	1.2 $\zeta_{(e,i)}$	12	3,600	14	11	36.5	11	3.8	30.5
I.13	MS	24	1.3 $\zeta_{(e,i)}$	17	3,600	41	13	1,699	13	128.3	132.7
I.14	Cost	10	$\zeta_{(e,i)}$	53,451	83.8	0	59,253	18.4	1,049,069	4.7	163.7
I.15	Cost	11	1.2 $\zeta_{(e,i)}$	62,591	2,872	0	65,592	15.4	301,088	6.2	39.8
I.16	Cost	13	1.3 $\zeta_{(e,i)}$	67,616	3,600	22.5	72,186	815	749,452	150	111

For the problem instances under makespan minimization, the minimum makespan found in integrated approach is equal to the minimum makespan found in the proposed decomposition strategy and sequential approach (i.e., I.01 to I.03 and I.11). For problem instances I.07, I.08, I.12 and I.13, the optimal makespan found in integrated approach is longer than that of sequential approach and decomposition strategy because: (i) to avoid purchases of utilities from external sources for problem instances I.07 and I.08, (ii) has reached maximum predefined time limit at high optimality gap for problem instances I.12 and I.13. Note that, there are purchases of utilities from external sources in decomposition strategy for problem instances I.07 and I.08. The total amount of purchases of utilities for decomposition strategy in these problem instances is 5 and 32 tons, respectively. Although decomposition strategy reports purchases of utilities for these problem instances, the amount of purchases of utilities is less than that of the sequential approach. However, there is no purchase of utilities is found in the solution of the proposed decomposition strategy for problem instances I.12 and I.13.

Finally, the computational experiment shows that the proposed decomposition strategy can achieve optimal or near-optimal solutions and a zero optimality gap at faster computational performance than that of the integrated approach. Although the optimal solution can only be achieved through integrated approach, it is computationally expensive to solve the planning problems to optimality especially for large MIP problems. In addition, integrated approach for solving large MIP problems may result to poor quality solutions if optimality cannot be guaranteed. For this reason, the proposed three-stage MIP-based decomposition strategy shows that the best solution and a zero optimality gap can be achieved at relatively low computational time.

### **3.6.3 A Case Study: Scheduling of Multistage Production System and Combined Heat and Power**

In this part, a case study for the scheduling problem of multistage production system and CHP-based utility system are solved through three-stage MIP-based decomposition strategy by using the proposed optimisation framework. The case

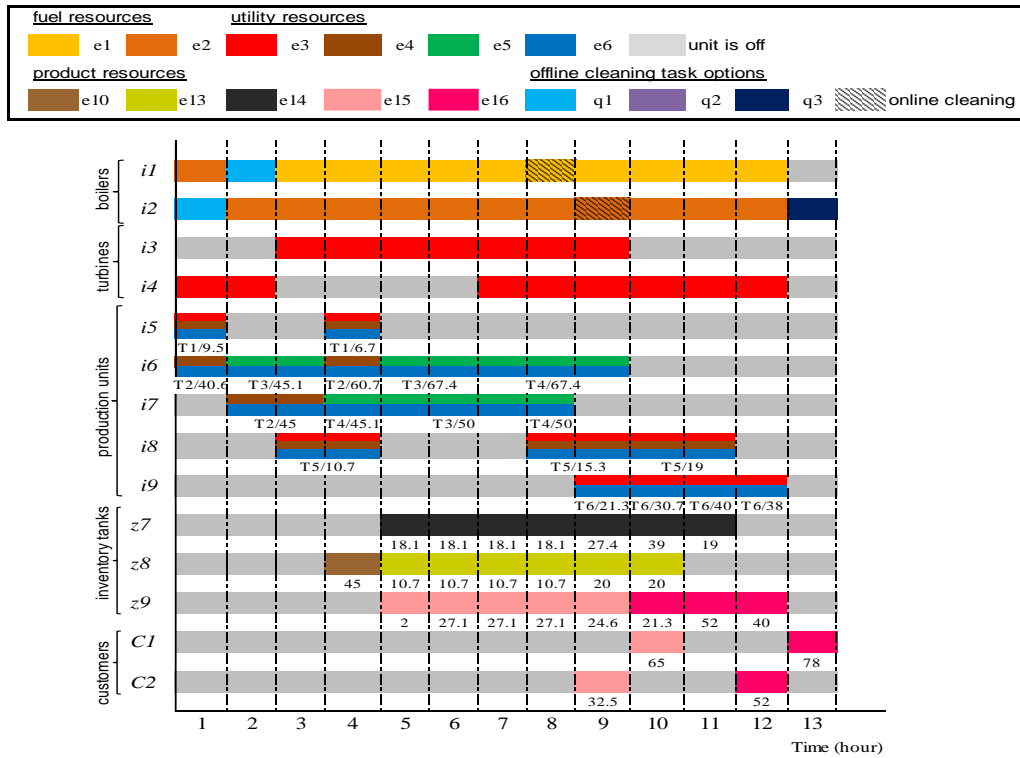
study considers condition-based cleaning policies for boilers in CHP-based utility system. This case study is presented in order to highlight special features of the proposed optimisation framework such as: (i) the occurrence of online and offline cleaning tasks for boilers in CHP-based utility system, (ii) variable processing time with respect to batch sizes, production tasks and production units, (iii) different types of utilities that are required by the production tasks in each production units. In this case study, no constraint on emissions cap is considered (i.e., emissions unconstrained case study).

### **3.6.3.1 Description of Case Study**

A modified version of the problem instance I.16 is considered. The main difference is there is no effect on the maximum operating level of boilers during online cleaning, the corresponding parameter  $\pi_i^{on}$  of these boilers are set equal to zero. The main parameters (Table 3-1 to Table 3-5), operational costs (Table 3-6), additional parameters for boilers and turbines (Table 3-7), parameters related to condition-based cleanings (Table 3-8 and Table 3-9) and initial states of the system (Table 3-10) are the same as before. The boilers and turbines are subject to startup and shutdown cost ( $I^{SF}$ ), minimum runtime ( $I^{S-\min}$ ) and shutdown time ( $I^{F-\min}$ ). In addition, the turbines are also subject to maximum runtime ( $MR_i$ ). A total planning horizon of 13 hours, divided in an hour time period is considered.

### **3.6.3.2 Results of Case Study**

This example has been solved by using the proposed decomposition strategy, and the results obtained are reported, analysed and discussed below.



**Figure 3-5 Optimal operational and cleaning schedule for multistage production system and CHP-based utility system**

Figure 3-5 displays the optimal operational and cleaning plan for the multistage production system and CHP-based utility system. More specifically, this figure shows for each unit per time period: (i) the operational status of boilers and turbines; (ii) the selected offline cleaning task options for boilers; (iii) the types of utility resources requirement from the production units; (iv) the batch size per production tasks in the production units; (v) the time for final products deliveries to the customers.

Boiler  $i1$  is operating using fuel resource  $e2$  (i.e.,  $\tilde{\chi}_{(e2,i1)}=1$ ) for about 10 hours (i.e.,  $\tilde{\rho}_{i1}=10$ ) before the beginning of current scheduling horizon (refer to Table 3-10). Boiler  $i1$  continues to consume fuel resource  $e2$  at the beginning of time period 1 before offline cleaning option  $q1$  takes place and then starts up at time period 3 by consuming fuel resource  $e1$ . Meanwhile, boiler  $i2$  that is operating using fuel resource  $e1$  (i.e.,  $\tilde{\chi}_{(e1,i2)}=1$ ) for about 10 hours (i.e.,  $\tilde{\rho}_{i2}=10$ ) before the

beginning of current scheduling horizon (refer to Table 3-10) shutdown at time period 1 to perform offline cleaning option  $q1$ . Boiler  $i2$  starts up to consume fuel resource  $e2$  at time period 2 until 12. At time period 13, boiler  $i2$  shutdown to perform offline cleaning option  $q3$  due to terminal constraints imposed on the minimum performance degradation rate for boilers at the end of time period. There are online cleanings for boiler  $i1$  and  $i2$  to partially restore their performance at time period 8 and 9, respectively.

Turbines  $i3$  and  $i4$  are subject to maximum runtime, minimum runtime and shutdown time. Notice that, turbine  $i3$  and  $i4$  have been continuously operating for 10 hours before the beginning of the scheduling horizon (i.e.,  $\tilde{\omega}_i=10$ ). At the beginning of the scheduling horizon, turbine  $i3$  shutdown for two hours before starts up at time period 3 and continues operating until at time period 9. Notice that, the total runtime for turbine  $i3$  is equal to 7 runtime that is between minimum (i.e.,  $\omega_{i3}=5$ ) and maximum runtime (i.e.,  $o_{i3}=12$ ). Meanwhile, turbine  $i4$  continues operating until at time period 2 before shutdown at the period 3. The total runtime for turbine  $i4$  is equal to 12 runtime which is less than the maximum runtime (i.e.,  $o_{i4}=14$ ). After more than 2 hours of minimum shutdown time (i.e.,  $\psi_{i4}=2$ ), turbine  $i4$  starts up at time period 7 and continues operating until it stops after time period 12.

At time period 1, production unit  $i5$  produces 9.5 kg of product  $e9$  through task  $T1$  and the production unit  $i6$  produces 40.6 kg of product  $e10$  through task  $T2$ . Then at time period 2, 4.5 kg of product  $e9$  and 40.6 kg of product  $e10$  are consumed by task  $T3$  in production unit  $i6$  and the remaining 5 kg of product  $e9$  is stored in inventory tank  $z6$ . Meanwhile, the production unit  $i7$  produces 45 kg of product  $e10$  through task  $T2$  at the end of time period 3 and then this product is stored in the inventory tank  $z8$  at time period 4.

The production unit  $i8$  produces 10.7 kg of product  $e13$  at the end of time period 4 and then store this product in the inventory tank  $z8$  at time period 5. Then at the same time period 5, production unit  $i7$  through the same task  $T3$  consumes

5 kg of product  $e_9$  from the inventory tank  $z_6$  and 45 kg of product  $e_{10}$  from the inventory tank  $z_8$  to produce 50 kg of product  $e_{11}$  at the end of time period 7. The same amounts of 50 kg of batch products are produced by task  $T_4$  in production unit  $i_7$  at the end of time period 8. This batch of products is split into 20 kg of product  $e_{14}$  and 30 kg of product  $e_{15}$ . The 30 kg of product  $e_{15}$  then goes to inventory tank  $z_9$  with inventory level of 27.1 kg. The 32.5 kg of the order of product  $e_{15}$  by the customer  $C_2$  is fulfilled through the inventory tank  $z_9$  at time period 9. The inventory level of product  $e_{15}$  in inventory tank  $z_9$  becomes 24.6 kg at the same time period.

Similarly at time period 5, 6.7 kg of product  $e_9$  and 60.7 kg of product  $e_{10}$  that are produced at the previous time period 4 are consumed by task  $T_3$  in production unit  $i_6$  in order to produce 67.4 kg of product  $e_{11}$  at the end of time period 6. Then, the same amounts of 67.4 kg of batch products are produced by task  $T_4$  in production unit  $i_6$  at the end of time period 9. This batch of products is split into 27 kg of product  $e_{14}$  and 40.4 kg of product  $e_{15}$ . The 40.4 kg of product  $e_{15}$  combines with the 24.6 kg of product  $e_{15}$  in the inventory tank  $z_9$  to satisfy the order of 65 kg of product  $e_{15}$  to the customer  $C_1$  at time period 10.

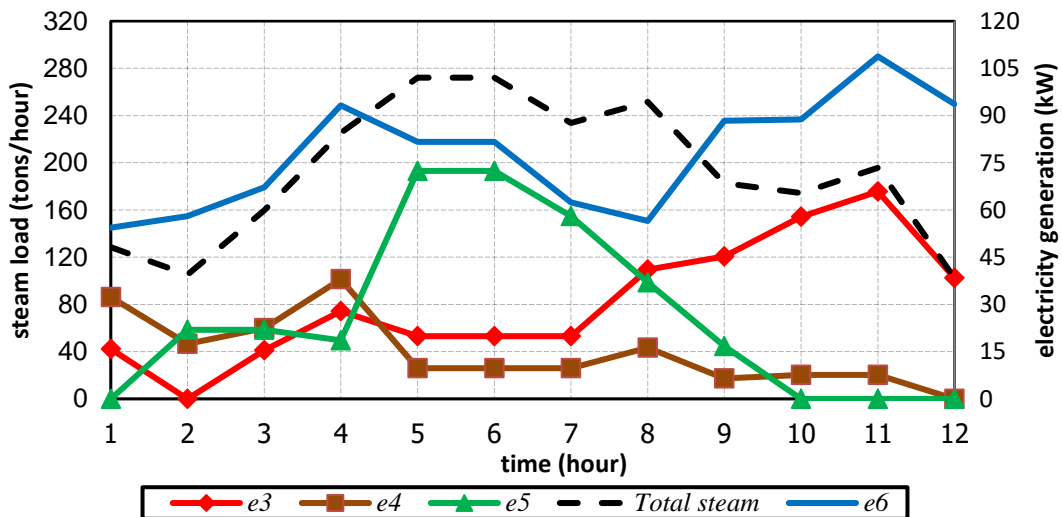
The production unit  $i_9$  through task  $T_6$  consumes 10.6 kg of product  $e_{14}$  from task  $T_4$  in production unit  $i_7$  and 10.7 kg of product  $e_{13}$  from inventory tank  $z_8$  to produce 21.3 kg of product  $e_{16}$  at the end of time period 9. Then, this 21.3 kg of product  $e_{16}$  is stored in inventory tank  $z_9$  at time period 10.

From the 20 kg of product  $e_{14}$  from task  $T_4$  in production unit  $i_7$ , 9.4 kg of it goes to inventory tank  $z_7$  and the remaining 10.6 kg is consumed by task  $T_6$  in production unit  $i_9$  at time period 9. In addition, task  $T_6$  in production unit  $i_9$  also consumes 10.7 kg of product  $e_{13}$  from inventory tank  $z_8$  to produce 21.3 kg of product  $e_{16}$  and then stores it in the inventory tank  $z_9$  at time period 10.

Similarly, from the 27 kg of product  $e_{14}$  from task  $T_4$  in production unit  $i_6$ , 11.6 kg of it is stored in inventory tank  $z_7$  and the remaining 15.4 kg is consumed by task  $T_6$  in production unit  $i_9$  at time period 10. The production unit  $i_8$  that

produces 15.3 kg of product  $e13$  at the end of time period 9 is also consumed by task  $T6$  in production unit  $i9$  at same time period. The total of 30.7 kg of product  $e16$  is produced at the end of time period 10 and then it is being stored in inventory tank  $z9$  at time period 11 and makes the total inventory level equals to 52 kg. The order of 52 kg of product  $e16$  by the customer  $C1$  is fulfilled from the inventory tank  $z9$  at time period 12.

Task  $T6$  in production unit  $i9$  continues to produce 40 kg and 38 kg of product  $e16$  at time period 11 and 12, respectively and then being stored in inventory tank  $z9$ . The order of 78 kg of product  $e16$  by the customer  $C1$  is fulfilled from the inventory tank  $z9$  at time period 13.

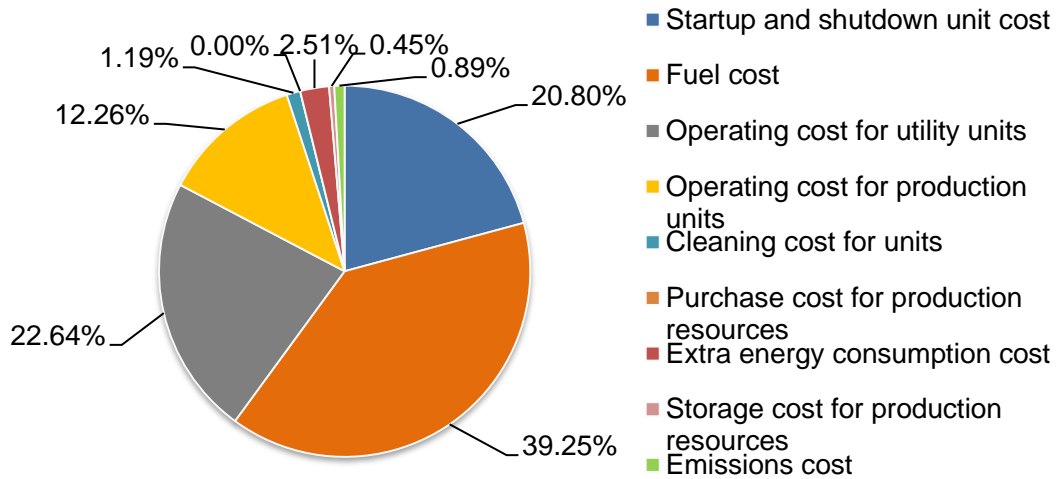


**Figure 3-6 Steam demand and electricity generation profiles of CHP-based utility system**

Figure 3-6 shows the steam demand and electricity generation profiles per time period of CHP-based utility system. The highest demand of the total steam that is needed by the production system is equal to 272 tons/hour at time period 5 and 6 due to high LP steam demand (i.e., utility resource  $e5$ ) at these time periods.

Meanwhile, the highest electricity generation to satisfy electricity demand is observed at time period 11 which is at about 109 kW. The electricity generation per time period increases above 60 kW from time period 9 to 12 due to the

production unit  $i9$  that processes task  $T6$  at these time periods has higher coefficient that provides the variable and fixed needs for electricity production than that of the other tasks (i.e.,  $\alpha_{(T6,i9,e6)}$  and  $\bar{\alpha}_{(T6,i9,e6)}$ , respectively) (refer also to Figure 3-5).



**Figure 3-7 Percentage of total cost breakdown**

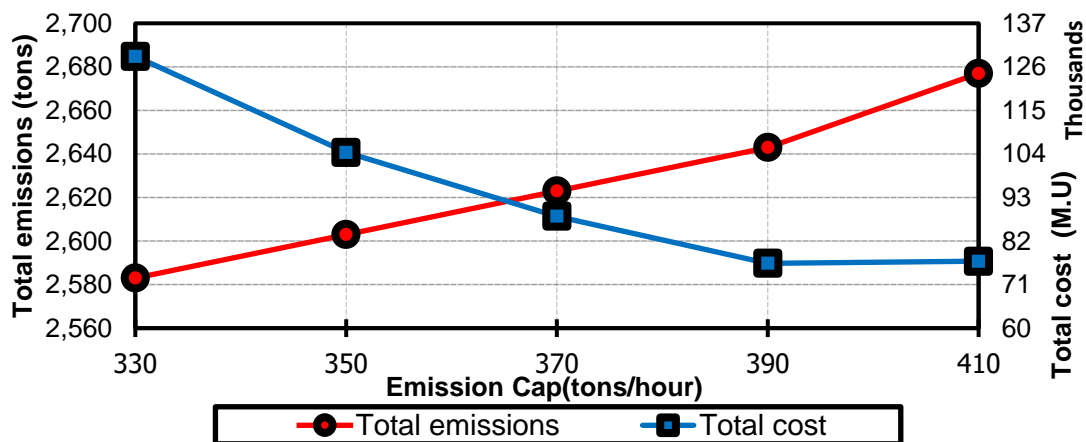
Figure 3-7 shows the breakdown of the total cost for the production system and CHP-based utility system. The costs are divided into: (i) the startup and shutdown operations for boilers and turbines; (ii) fuel consumption by the boilers ; (iii) the operation of the CHP-based utility system; (iv) the operation of the multistage production system; (v) offline and online cleaning tasks for the boilers; (vi) the total purchase of utility resources; (vii) extra energy consumption of the boilers under condition-based cleaning policy; (viii) storage for production resources; and (ix) emissions from the use of fuel in the boilers. The fuel cost is the highest cost term at about 39% of the total cost. The second highest cost is the operating cost for utility units (i.e., boilers and turbines) in CHP-based utility system which is about 22.6% of the total cost. The startup and shutdown cost for boilers and turbines in CHP-based utility system are around 21% of the total cost. The operational cost for production system is 12%. Meanwhile, the extra energy consumption cost and cleaning cost for the boilers are about 2.5% and 1.2% of the total cost, respectively. The emissions cost and storage cost for production



resources are only about 0.89% and 0.45% of total cost, respectively. Meanwhile, there is no purchase cost for all utility resources.

### 3.6.4 The Effect of Emissions Caps

In this example, a slightly modified illustrative case study is considered by imposing an upper bound on the quantity of emissions for CO<sub>2</sub> and SO<sub>x</sub>. The maximum amount of emissions per time period in the solution of the illustrative case study is 397 tons per time period. In this example, different upper bound on the quantity of total emissions per time period is set.



**Figure 3-8 Sensitivity analysis for total emissions and cost under different emissions caps**

Sensitivity analysis is performed to study the trade-offs between total emissions and total cost under varied emission cap per time period as shown in Figure 3-8. It is observed that total cost increases significantly for emission caps below 360 tons per hour. The minimum possible emissions cap is 365 tons per hour since below this emission cap, the purchase cost for utility resources becomes unreasonably high. With respect to the emissions unconstrained case study, the minimum possible emissions cap considered can achieve emissions reductions of 1.2% with resulting to total cost increases to 27%. The emissions reduction is achieved through the use of fuels in the boilers with lower coefficient of CO<sub>2</sub> emissions (Table 3-1). It needs to be highlighted that the total emissions are affected to the higher extent by the emissions of CO<sub>2</sub> rather than the emissions

of SO<sub>x</sub>. This is because the coefficient of emissions for CO<sub>2</sub> is generally higher than that for SO<sub>x</sub> when the fuel is used in the boilers ( $\alpha_{(e',e)}^{EMIS}$ ). In this case study, the optimisation results favour the use of the fuel *e2* over the fuel *e1*. As a result, the total cost increases due to higher emission costs from the use of fuel *e2* that has slightly higher coefficient of emissions for SO<sub>x</sub> and the minor purchase of electricity.

### 3.7 Conclusions

In this study, three-stage MIP-based decomposition strategy has been introduced for integrated planning of multistage production system and CHP-based utility system. The optimisation framework considers complex production processes such as varied task duration of the batch size, batching restriction for product resources, and the need of different utilities of the same tasks. In addition, unit performance degradation and recovery for the units under condition-based cleaning has also been considered. In the computational experiments solved, it is observed that the proposed three-stage MIP-based decomposition strategy can achieve optimal or near-optimal solutions and a zero optimality gap with faster computational performance than that of the integrated approach. It has also been demonstrated that potential reductions in emissions for the minimum possible emission cap have been achieved through the use of fuel in the boilers with lower coefficient of emissions for greenhouse gases (e.g., CO<sub>2</sub>). The proposed MIP-based decomposition strategy combines the benefits of faster computational time of the sequential approach and superior productivity that is offered by the integrated approach. In a real industrial process, integrated approach might be difficult to implement due to the need for extensive computational performances and transparent data integration across the planning management of the production and utility systems. Therefore, the proposed MIP-based decomposition strategy provides an intermediate approach for an effective planning approach in order to properly address real industrial scenarios of production and utility systems.

# 4 A ROLLING-HORIZON STOCHASTIC PROGRAMMING APPROACH FOR THE INTEGRATED PLANNING OF PRODUCTION AND UTILITY SYSTEMS <sup>c</sup>

## 4.1 Abstract

This study focuses on the operational and resource-constrained condition-based cleaning planning problem of integrated production and utility systems under uncertainty. For the problem under consideration, a two-stage scenario-based stochastic programming model that follows a rolling horizon modelling representation is introduced, resulting in a hybrid reactive-proactive planning approach. In the stochastic programming model, all the binary variables related to the operational status (i.e., startup, operating, shutdown, under online or offline cleaning) of the production and utility units are considered as first-stage variables (i.e., scenario independent), and most of the remaining continuous variables are second-stage variables (i.e., scenario dependent). In addition, enhanced unit performance degradation and recovery models due to the cumulative operating level deviation and cumulative operating times are presented. Terminal constraints for minimum inventory levels for utilities and products as well as maximum unit performance degradation levels are also introduced. Two case studies are presented to highlight the applicability and the particular features of the proposed approach as an effective means of dealing with the sophisticated integrated planning problem considered in highly dynamic environments.

## 4.2 Introduction

The process industry is a key economic sector globally. The global market share and business performance of the process industry is heavily based on the value that can be generated from its assets and while the range of valuable assets is

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<sup>c</sup> Zulkafli, N.I. and Kopanos, G.M. (2018a) 'A rolling-horizon stochastic programming approach for the integrated planning of production and utility systems', *Chemical Engineering Research and Design*, 139, pp. 224 - 247.

large, nearly all the economic value in terms of operating profit in the process industry is a direct result of operations of plant equipment (Christofides et al., 2007). Also, major plant equipment constitutes highly expensive capital assets that are typically subject to performance degradation and require periodic maintenance to avoid their damage or inefficient operation. Typically, maintenance planning follows very conservative approaches and is done separately from the production planning. Such approaches result in increased needs for maintenance resources (and associated costs), material waste, and productivity losses. All these, make clear the imperative need for systematic approaches for the efficient management of equipment operations and maintenance to preserve the major assets of a process industry and increase financial gains and competitiveness.

In process industries, a sequential approach is typically used for the operational planning of utility and production systems. First, the planning of the production system is performed considering simply the upper bounds on the availability of utilities. Once the production plan is derived, the utility needs of the production are known. Second, this information is then used to obtain the operational planning of the utility system. This sequential approach provides suboptimal solutions (mainly in terms of resource and energy efficiency and costs) because the two interconnected systems are not optimised at the same time. Importantly, the sequential approach often faces the risk of providing utilities generation targets that cannot be met by the energy system (i.e., infeasible solutions), and in that case a re-planning of the production system is usually employed (Zulkafli and Kopanos, 2016). What is more, conservative maintenance planning is usually performed separately from operational planning which typically does not consider the dynamic condition of the equipment.

This chapter is organised as follows. Section 4.3 provides a brief literature review. The formal statement of the problem under study is defined in Section 4.4. The proposed optimisation framework is presented in Section 4.5 followed by two case studies in Section 4.6. Finally, concluding remark is provided in Section 4.7.

### 4.3 Literature Review

Modern process industries operate in highly dynamic environments that usually involve significant fluctuations on key operational, costs and market related parameters (e.g., demand fluctuations, prices variations or unit breakdowns). This makes essential the development and use of efficient planning approaches to deal with such types of uncertainties. There are two major types of planning approaches to deal with uncertainties, namely reactive and proactive approaches. In general, reactive approaches involve the repetitive solution of the deterministic planning problem within a rolling horizon framework, and are especially suitable for highly dynamic environments with limited information about the behaviour of the uncertainty (Zulkafli and Kopanos, 2017). In simple words, these approaches basically rely on a wait and react approach with respect to unexpected events. Proactive approaches are typically used when some information about the behaviour of the uncertainty is available, and their purpose is to provide solutions that will be immune to uncertainty. These approaches rely on an act before it happen basis. Stochastic programming or robust optimisation is usually used in proactive planning approach. In general, proactive approaches propose more conservative solutions in comparison with reactive approaches, and are more suitable for less flexible environments in terms of changing frequently major operational decisions.

A number of works that proposed proactive approaches for operational planning problems can be found in the open literature. For example, Cobuloglu and Esra Büyüktaktın (2017) proposed a two-stage stochastic programming model for maximizing economic and environmental aspects of food and biofuel production under yield and prices uncertainty. Choi et al. (2016) presented a stochastic programming model under a Monte-Carlo simulation to develop a multi-period energy planning model under uncertainty in market prices and demands for energy resources. Huang, Wu and Hsu (2016) presented a two-stage stochastic programming model for the electricity planning under demand uncertainty. Kostin et al. (2012) studied a multi-scenario problem on the design and planning of integrated bioethanol-sugar supply chains under demand uncertainty. Other

works have developed proactive approaches for cleaning planning problems. For instance, Gössinger, Helmke and Kaluzny (2017) presented a condition-based cleaning policy to deal with stochastic deterioration processes. In the same line, Samuelson et al. (2017) presented a stochastic programming model for different cleaning strategies in continuously deteriorating systems. A two-stage nonlinear stochastic programming model for production and cleaning planning with yield and demand uncertainty was proposed by Ekin (2017) while Khatab et al. (2017) studied the cleaning planning problem for a multi-component system with stochastic durations of alternative cleaning actions. Zhou et al. (2016) presented an optimal cleaning policy of a parallel-series system considering stochastic and economic dependence under limited cleaning resources. The optimal cleaning schedule for heat exchanger network in an oil refinery under fouling and different aging scenarios was studied by Diaby, Miklavcic and Addai-Mensah (2016) while Biyanto et al. (2016) used different stochastic optimisation methods developed for the optimal cleaning schedule in crude preheat trains. Among a limited number of works that combine reactive and proactive approaches, Silvente et al. (2015) developed a rolling horizon stochastic programming approach for the energy supply and demand management of microgrids. The authors further developed their model to consider a rolling horizon approach for optimal management of microgrid under stochastic uncertainty (Silvente et al. 2018). In addition, Gupta and Maranas (2000) studied a two-stage stochastic programming model to solve supply-chain planning problem under demand uncertainty through a rolling horizon framework.

In fact, most of the previous studies have separately addressed the operational planning problems or cleaning planning problems (i.e., sequential approach) under uncertainty for either utility or production system. A brief literature reviews on sequential approaches in process industries and a discussion on the need for integrated plant-wide planning approaches can be found in Zulkafli and Kopanos (2016). Importantly, Zulkafli and Kopanos (2017) showed that significant total cost reductions (from 5% to 32%) can be achieved if an integrated planning approach is used instead of the sequential alternative. Therefore, there is an important need

for development of integrated planning approaches that also account efficiently for uncertainty to deal with the dynamic nature of the process industries.

This chapter presents a two-stage scenario-based stochastic programming approach for the integrated planning of utility and production systems under uncertainty. It is assumed that some information about the behavior of the uncertainty parameters is known (i.e., number of scenarios with associated probability of occurrence, and given parameter values for each scenario). In particular, this study is a major extension of the previous work in Chapter 2 by: (i) providing a two-stage scenario-based stochastic programming version of a modification of the previously deterministic model, (ii) introducing an improved cumulative operating level deviation model for condition-based cleaning policies, (iii) defining improved terminal constraints for the maximum allowable unit performance degradation level (i.e., minimum performance level) at the end of the planning horizon, (iv) incorporating the resulting two-stage scenario-based stochastic programming model into a rolling horizon framework to readily deal with various types of uncertainties. The proposed approach follows a plant-wide condition-based approach for the cleaning actions that explicitly consider the condition of the units as a result of the optimised operational planning of the production and utility systems. This is the first work that proposes a rolling horizon stochastic programming approach for the simultaneous operational and condition-based planning for integrated production and utility systems.

#### **4.4 Problem Statement**

This work focuses on the stochastic version of the integrated operational and condition-based cleaning planning of production and utility systems under alternative resource-constrained cleaning policies, by considering performance degradation and recovery for utility and production units. Demand profiles for products are considered as the uncertain parameters of the problem in question, and it is assumed that they can be modelled by defining a number of different scenarios with given probability of occurrence. This results into a two-stage

scenario-based stochastic programming planning problem which is formally defined in terms of following items:

- A given planning horizon divided into a number of equally-length time period  $t \in T$ .
- A set of scenarios  $n \in N$  with given probability of occurrence for each scenario  $\delta_n^p$ .
- A set of resources  $e \in E$  that are divided into product ( $e \in E^{PR}$ ) and utilities ( $e \in E^{UT}$ ).
- Given demand profiles for products per scenario  $\zeta_{(n,e,t)}$  (i.e., stochastic parameter).
- A set of units  $i \in I$  that are classified to utility ( $i \in UT_i$ ) and production ( $i \in PR_i$ ) units and could produce a number of resources  $e \in E$ . Maximum (minimum) operating levels  $\kappa_{(i,t)}^{\max}$  ( $\kappa_{(i,t)}^{\min}$ ) for utility units and production levels  $\bar{\kappa}_{(e,i,t)}^{\max}$  ( $\bar{\kappa}_{(e,i,t)}^{\min}$ ) for production units are given. For every unit that is subject to startup and shutdown actions ( $i \in I^{SF}$ ), the startup ( $\phi_{(i,t)}^S$ ) and shutdown ( $\phi_{(i,t)}^F$ ) costs are also given. For any unit that is subject to minimum runtime and shutdown time restrictions (i.e.,  $i \in I^{S-\min}$  and  $i \in I^{F-\min}$ , respectively), the minimum runtime after its last startup  $\omega_i$  and the minimum idle time after its last shutdown  $\psi_i$  are also defined.
- A set of resource-dedicated inventory tanks  $i \in IT_e$  that can receive resources from units  $i \in ZI_i^+$  and send resources to units  $i \in ZI_i^-$ . The inventory tanks have a given maximum (minimum): inventory tank level  $\beta_{(e,i)}^{\max}$  ( $\beta_{(e,i)}^{\min}$ ), inlet resource flow  $\beta_{(e,i,t)}^{-,\max}$  ( $\beta_{(e,i,t)}^{+,\min}$ ), and outlet utility resource flow  $\beta_{(e,i,t)}^{-,\max}$  ( $\beta_{(e,i,t)}^{-,\min}$ ). Initial inventory tank levels  $\tilde{\beta}_{(e,i)}$  and losses coefficients  $\beta_i^{loss}$  are also given.
- Different cleaning policies for the units are considered. In particular, a unit could be subject to: (i) flexible time-window offline cleaning ( $i \in FM_i$ ) with



a given earliest  $\tau_i^{es}$  and latest  $\tau_i^{ls}$  starting time, (ii) in-progress offline cleaning carried over from the previous planning horizon ( $i \in DM_i$ ), or (iii) condition-based cleaning ( $i \in CB_i$ ) with known performance degradation rates. Two types of condition-based cleaning tasks are considered, namely: online cleaning tasks ( $CB_i^{on}$ ) with given recovery factors  $\rho_i^{rec}$ , and offline cleaning tasks ( $CB_i^{off}$ ).

- A set of alternative cleaning tasks options  $q \in Q_i$  for each unit that is subject to flexible time-window cleaning ( $i \in FM_i$ ) or offline condition-based cleaning ( $i \in CB_i^{off}$ ). The cleaning tasks options are characterised by different durations  $v_{(i,q)}$ , cleaning resource requirements  $g_{(i,q)}^{off}$ , and associated cleaning costs  $\phi_{(i,q,t)}^{off}$ .
- For every production unit  $i \in I_e^{PR}$ , fixed and variable utility needs for the production of products are given ( $\bar{\alpha}_{(i,e,e')}$  and  $\alpha_{(i,e,e')}$ , respectively).
- Given variable and fixed operating costs for production and utility units,  $\phi_{(i,e,t)}^{PR,op-var}$  and  $\phi_{(i,e,t)}^{PR,op-fix}$ , and  $\phi_{(i,t)}^{UT,op-var}$  and  $\phi_{(i,t)}^{UT,op-fix}$ , respectively.
- Given purchase prices for acquiring utilities and products from external sources,  $\phi_{(e,i,t)}^{UT,ex}$  and  $\phi_{(e,t)}^{PR,ex}$ , respectively.
- A given time-varying energy price profile  $\phi_{(i,t)}^{pw}$ .

For the planning horizon considered, the optimisation goal is to minimise the total cost which mainly includes unit operational and cleaning costs and resource purchases. In order to achieve this, for every time period, the key decisions to be optimised are: the operational status of each production and utility unit (i.e., startup, shutdown, in operation, idle, under online or offline cleaning); the selection of the timing and the offline cleaning task option for each unit; the operating level for each production and utility unit for each scenario; the inventory level for utilities and product resources for each scenario; and the utility requirements per scenario for each production unit.

The decision variables of the two-stage scenario-based stochastic programming problem under consideration are divided in first-stage and second-stage variables as shown below.

First-stage variables (i.e., scenario independent):

- $X_{(i,t)} = \begin{cases} 1 & \text{if unit } i \text{ is operating during time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $S_{(i,t)} = \begin{cases} 1 & \text{if unit } i \text{ starts up at the beginning of time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $F_{(i,t)} = \begin{cases} 1 & \text{if unit } i \text{ shuts down at the beginning of time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $H_{(i,q,t)} = \begin{cases} 1 & \text{if cleaning task option } q \text{ for } i \in (CB_i^{off} \cup FM_i) \text{ begins at the start of time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $W_{(i,t)} = \begin{cases} 1 & \text{if an offline cleaning task for } i \in (CB_i^{off} \cup FM_i) \text{ begins at the start of time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $V_{(i,t)} = \begin{cases} 1 & \text{if an online cleaning task for } i \in (CB_i^{on} \cap UT_i) \text{ takes place in time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $V_{(i,e,t)}^{PR} = \begin{cases} 1 & \text{if an online cleaning task for } i \in (CB_i^{on} \cap PR_i) \text{ that produces } e \in E_i \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $Y_{(e,i,t)} = \begin{cases} 1 & \text{if production unit } i \in PR_i \text{ produces product } e \text{ during time period } t, \\ 0 & \text{otherwise.} \end{cases}$
- $R_{(i,t)}$ : cumulative time of operation for units subject to condition-based cleaning.

Second-stage variables (i.e., scenario dependent):

- Operating levels for utility units  $QS_{(n,i,t)}$ .
- Production levels for utilities and products from their respective unit  $QE_{(n,e,i,t)}$ .
- Inventory levels for utilities and products  $B_{(n,e,i,t)}$ .
- Total inlet flow of utilities and products to their respective inventory tanks  $B_{(n,e,i,t)}^+$ .
- Total outlet flow of utilities and products from their respective inventory tanks  $B_{(n,e,i,t)}^-$ .
- Extra energy consumption of units due to their performance degradation  $U_{(n,i,t)}$ .

- Cumulative operating level deviation for units subject to condition-based cleaning  $D_{(n,i,t)}$ .
- Operating level deviations of production units from their reference operating level  $Q_{(n,e,i,t)}^{dev}$ .
- Operating level deviations of utility units from their reference operating level  $\bar{Q}_{(n,i,t)}^{dev}$ .
- Purchases of utilities  $NS_{(n,e,i,t)}^{UT}$  or products  $NS_{(n,e,t)}^{FP}$ .

## 4.5 Optimisation Framework

This part presents the proposed stochastic programming model for the integrated planning problem described in the previous section. This stochastic programming model follows a rolling-horizon modelling representation, and that way results in a hybrid reactive-proactive planning approach, when applied within a rolling-horizon scheme. Figure 4-1 shows a schematic representation of the steps of the proposed planning approach that work as follows. First, one needs to define a number of scenarios with assigned probabilities of occurrence and specified values for the uncertain parameters considered. Next, a prediction horizon is defined for which the stochastic programming model is solved. The length of the prediction horizon depends on the quality of the available information of the uncertain parameters. In the rolling-horizon approach, it is implemented in practice the solution of a limited number of periods (i.e., usually just that of the first time period of the prediction horizon) that have been considered in the prediction horizon.

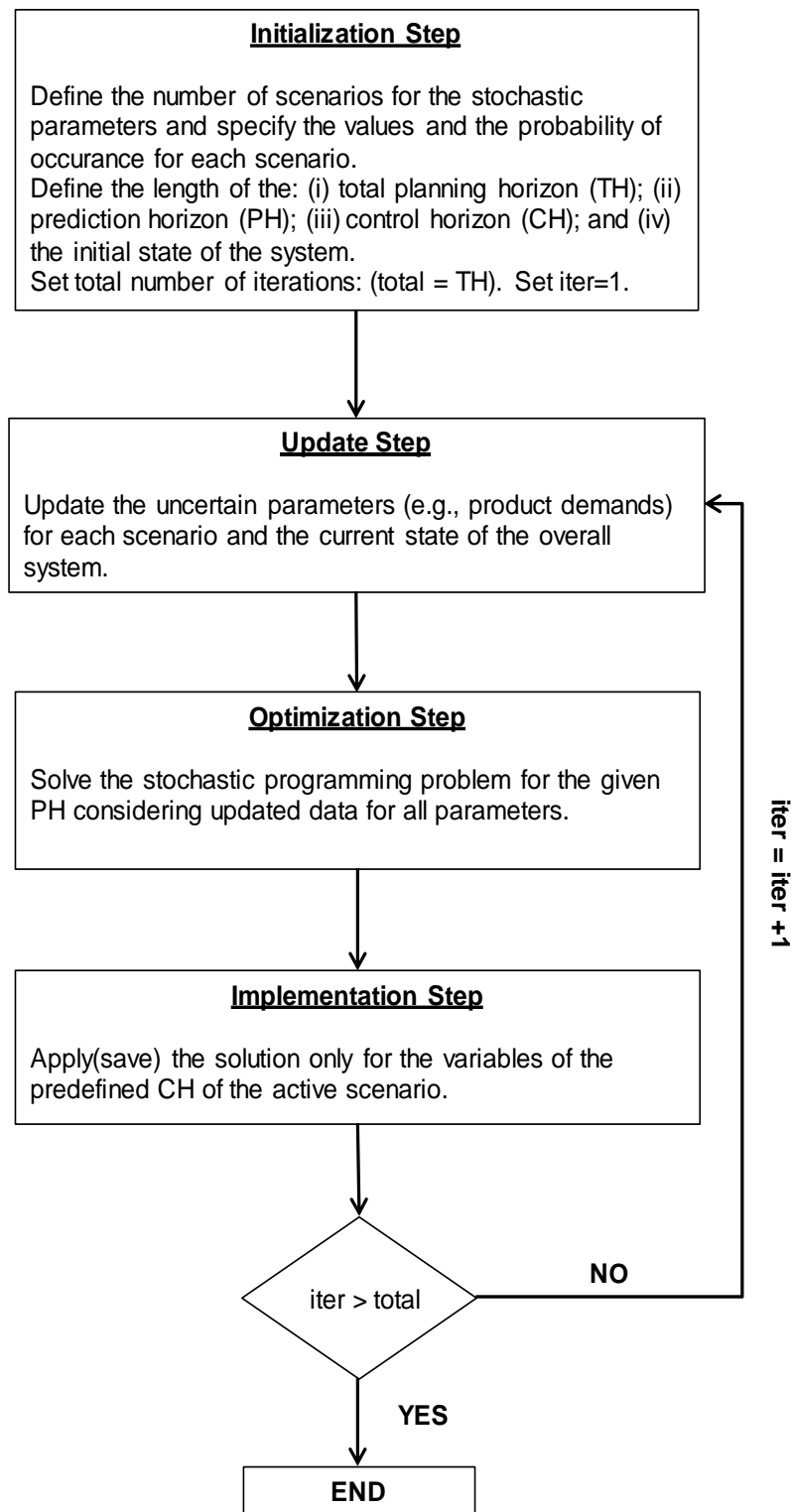


Figure 4-1 Planning via a rolling horizon stochastic programming method

In such approaches, it is essential to update properly the initial state of the overall system before solving the optimisation problem for the given prediction horizon. Especially, if a scenario-based stochastic approach is used, the active scenario (i.e., scenario that eventually occurred) should be known/defined and update the initial state of the system with respect to this active scenario. In this study, the main parameters that describe the initial state of the overall system are: (i) the inventory levels for utilities and products; (ii) the cumulative time of operation for each unit; (iii) the cumulative operating level deviation for each unit; (iv) the current operating status of each unit; (v) the startup and shutdown history of each unit; (vi) the online and offline cleaning history of each unit; (vii) the cleaning resources history of units; and (viii) the demands for products per scenario considered. A more detailed description and discussion on the reactive planning via a rolling horizon framework can be found in Chapter 2.

The stochastic programming model presented is an enhanced modified version of the deterministic model of the previous work in Chapter 2. For this reason, constraints that remain unchanged from its deterministic version, proper references will be given to the constraints of the previous work to avoid unnecessary repetitions. A description of the proposed optimisation framework follows.

#### **4.5.1 Major Operational and Cleaning Decisions**

Constraints related to major operational and cleaning decisions are modelled through first-stage binary variables. These constraints are the same with those of the deterministic version of the model presented in the previous work. More specifically, the stochastic programming model includes constraints (2-1) to (2-10) and (2-24) to (2-26) from Chapter 2. These constraints model: (i) minimum run and shutdown periods; (ii) in-progress offline cleaning tasks; (iii) flexible time-window offline cleaning tasks; (iv) condition-based online cleaning tasks; (v) operational constraints for offline cleaning tasks; and (vi) resource limitations for cleaning resources.

#### 4.5.1.1 Performance Degradation and Recovery Models for Units

For each scenario, the performance of any unit that is subject to condition-based cleaning is modelled through the extra energy consumption  $U_{(n,i,t)}$  due to its deviation from its completely clean condition. It is assumed that the performance of a unit decreases as this extra energy consumption increases. To avoid the energy inefficient use and potential damage of the unit, this extra energy consumption for the units under operation should not exceed a maximum extra energy consumption limit  $v_i^{\max}$ , as defined by:

$$U_{(n,i,t)} \leq v_i^{\max} X_{(i,t)} \quad \forall n \in N, \forall i \in CB_i, \forall t \in T \quad (4-1)$$

The extra energy consumption of an operating unit is related to its cumulative time of operation  $R_{(i,t)}$  and its cumulative operating level deviation  $D_{(n,i,t)}$ , through parameters  $\delta_i$  and  $\delta_i^{cd}$  that represent the corresponding degradation rates, as given by:

$$\begin{aligned} U_{(n,i,t)} &\geq \delta_i R_{(i,t)} + \delta_i^{cd} D_{(n,i,t)} - v_i^{\max} (1 - X_{(i,t)}) & \forall n \in N, \forall i \in CB_i, \forall t \in T \\ U_{(n,i,t)} &\leq \delta_i R_{(i,t)} + \delta_i^{cd} D_{(n,i,t)} + v_i^{\max} (1 - X_{(i,t)}) & \forall n \in N, \forall i \in CB_i, \forall t \in T \end{aligned} \quad (4-2)$$

##### 4.5.1.1.1 Cumulative time of operation

The variables that describe the cumulative time of operation are first-stage variables, and the corresponding constraints considered are the same with the deterministic constraints (2-11) to (2-16) in Chapter 2.

##### 4.5.1.1.2 Cumulative operating level deviation

The variables that describe the cumulative operating level deviation are second-stage variables, and the corresponding constraints are presented here. First, similarly to the cumulative time of operation, the occurrence of an offline cleaning task in a unit resets its cumulative operating level deviation to zero, as defined by:

$$D_{(n,i,t)} \leq \mu_{(i,t)} (1 - W_{(i,t)}) \quad \forall n \in N, \forall i \in CB_i^{off}, \forall t \in T \quad (4-3)$$

Parameters  $\mu_{(i,t)}$  are sufficiently large numbers that could be calculated through the corresponding maximum extra energy consumption and degradation rate parameters.

In comparison with the previous reseach work, improved sets of constraints for the modelling of the cumulative operating level deviation for units subject to condition-based cleaning is presented. More specifically, in this study the cumulative operating level deviation of a unit resets to zero only after the occurrence of an offline cleaning task while in the previous work it was assumed that this happens after the shutdown of the unit.

The new sets of constraints for the modelling of the cumulative operating level deviation of utility units subject to condition-based cleaning are presented below:

$$\begin{aligned}\bar{Q}_{(n,i,t)}^{dev} &\leq \left( \frac{|q_{(i,t)}^{ref} - QS_{(n,i,t)}|}{q_{(i,t)}^{ref}} \right) + \mu_{(i,t)}(1 - X_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T \\ \bar{Q}_{(n,i,t)}^{dev} &\geq \left( \frac{|q_{(i,t)}^{ref} - QS_{(n,i,t)}|}{q_{(i,t)}^{ref}} \right) - \mu_{(i,t)}(1 - X_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T \\ \bar{Q}_{(n,i,t)}^{dev} &\leq \mu_{(i,t)} X_{(i,t)} \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T\end{aligned}\tag{4-4}$$

$$\begin{aligned}D_{(n,i,t)} &\leq \tilde{\rho}_i^{cd} + \bar{Q}_{(n,i,t)}^{dev} + \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T : t = 1 \\ D_{(n,i,t)} &\leq D_{(n,i,t-1)} + \bar{Q}_{(n,i,t)}^{dev} + \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T : t > 1\end{aligned}\tag{4-5}$$

$$\begin{aligned}D_{(n,i,t)} &\geq \tilde{\rho}_i^{cd} + \bar{Q}_{(n,i,t)}^{dev} - \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T : t = 1 \\ D_{(n,i,t)} &\geq D_{(n,i,t-1)} + \bar{Q}_{(n,i,t)}^{dev} - \mu_{(i,t)}(W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap UT_i), t \in T : t > 1\end{aligned}\tag{4-6}$$

$$\begin{aligned}D_{(n,i,t)} &\geq (\tilde{\rho}_i^{cd} + \bar{Q}_{(n,i,t)}^{dev})(1 - \rho_i^{rec}) - \mu_{(i,t)}(1 - V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i^{on} \cap UT_i), t \in T : t = 1 \\ D_{(n,i,t)} &\geq (D_{(n,i,t-1)} + \bar{Q}_{(n,i,t)}^{dev})(1 - \rho_i^{rec}) - \mu_{(i,t)}(1 - V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i^{on} \cap UT_i), t \in T : t > 1\end{aligned}\tag{4-7}$$

New variables  $\bar{Q}_{(n,i,t)}^{dev}$  have been defined to describe the additional cumulative operating level deviation at each time period from a reference operating level  $q_{(i,t)}^{ref}$ . That way the cumulative operating level deviation variables  $D_{(n,i,t)}$  do not reset to zero whenever a unit shuts down (i.e., if  $X_{(i,t)} = 0$ , then  $\bar{Q}_{(n,i,t)}^{dev} = 0$  and

$D_{(n,i,t)} = D_{(n,i,t-1)}$ ). The cumulative operating level deviation can be reset to zero if and only if a utility unit undergoes offline cleaning. Under online cleaning periods, the cumulative operating level deviation of a utility unit is reduced partially by a given recovery factor, as defined by constraints (4-7). In order to avoid the non-linear expressions in the model, the reference operating level  $q_{(i,t)}^{ref}$  is assumed to be the maximum operating level ( $\kappa_{(i,t)}^{max}$ ).

In the same line, the cumulative operating level deviation of production units subject to condition-based cleaning is modelled by the new sets of constraints presented below:

$$\begin{aligned} Q_{(n,e,i,t)}^{dev} &\leq \left( \frac{q_{(e,i,t)}^{ref} - QE_{(n,e,i,t)}}{q_{(e,i,t)}^{ref}} \right) + v_i^{max} (1 - Y_{(e,i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), e \in E_i, t \in T \\ Q_{(n,e,i,t)}^{dev} &\geq \left( \frac{q_{(e,i,t)}^{ref} - QE_{(n,e,i,t)}}{q_{(e,i,t)}^{ref}} \right) - v_i^{max} (1 - Y_{(e,i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), e \in E_i, t \in T \end{aligned} \quad (4-8)$$

$$Q_{(n,e,i,t)}^{dev} \leq \mu_{(i,t)} Y_{(e,i,t)} \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), e \in E_i, t \in T$$

$$\begin{aligned} D_{(n,i,t)} &\leq \tilde{\rho}_i^{cd} + \sum_{e \in E_i} Q_{(n,e,i,t)}^{dev} + \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), t \in T : t = 1 \\ D_{(n,i,t)} &\leq D_{(i,t-1)} + \sum_{e \in E_i} Q_{(n,e,i,t)}^{dev} + \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), t \in T : t > 1 \end{aligned} \quad (4-9)$$

$$\begin{aligned} D_{(n,i,t)} &\geq \tilde{\rho}_i^{cd} + \sum_{e \in E_i} Q_{(n,e,i,t)}^{dev} - \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), t \in T : t = 1 \\ D_{(n,i,t)} &\geq D_{(i,t-1)} + \sum_{e \in E_i} Q_{(n,e,i,t)}^{dev} - \mu_{(i,t)} (W_{(i,t)} + V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i \cap PR_i), t \in T : t > 1 \end{aligned} \quad (4-10)$$

$$\begin{aligned} D_{(n,i,t)} &\geq \left( \tilde{\rho}_i^{cd} + \sum_{e \in E_i} Q_{(n,e,i,t)}^{dev} \right) (1 - \rho_i^{rec}) - \mu_{(i,t)} (1 - V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i^{on} \cap PR_i), t \in T : t = 1 \\ D_{(n,i,t)} &\geq \left( D_{(i,t-1)} + \sum_{e \in E_i} Q_{(n,e,i,t)}^{dev} \right) (1 - \rho_i^{rec}) - \mu_{(i,t)} (1 - V_{(i,t)}) \quad \forall n \in N, \forall i \in (CB_i^{on} \cap PR_i), t \in T : t > 1 \end{aligned} \quad (4-11)$$

For every unit, parameter  $\tilde{\rho}_i^{cd}$  represents its cumulative operating level deviation just before the beginning of the planning horizon of interest (i.e., initial state).



## 4.5.2 Utility and Production Units: Operating Levels Bounds

### 4.5.2.1 Utility System

The utility system consists of a number of utility units that could generate a number of utility resources required by the production system. The operating level for each operating utility unit per scenario should be between its lower and upper operating level bounds ( $\kappa_{(i,t)}^{\min}$  and  $\kappa_{(i,t)}^{\max}$ ). The maximum operating levels during online cleaning periods are modelled as discussed in Chapter 2. The operating bounds are given by:

$$\kappa_{(i,t)}^{\min} X_{(i,t)} \leq QS_{(n,i,t)} \leq \kappa_{(i,t)}^{\max} (X_{(i,t)} - \pi_i^{on} V_{(i,t)}) \quad \forall i \in (UT_i \cap CB_i^{on}), t \in T \quad (4-12)$$

Some types of utility units, such as combined heat and power units, generate at the same time more than one utility resources. The generated amount of any utility resource from each utility unit per scenario and time period is modelled by:

$$QE_{(n,e,i,t)} = \rho_{(e,i)}^{COGEN} QS_{(n,i,t)} \quad \forall n \in N, \forall i \in UT_i, e \in E_i, t \in T \quad (4-13)$$

Parameters  $\rho_{(e,i)}^{COGEN}$  denote the stoichiometry coefficients that relate the operating level of the utility unit with the generated amount of each utility resource type ( $QE_{(n,e,i,t)}$ ) that is cogenerated by the same utility system (e.g., heat to power ratio of a combined heat and power unit).

### 4.5.2.2 Production System

This study considers a single-stage production process with a number of different units operating in parallel for producing the whole set of desired products. Similarly to utility units, changes in the maximum production levels during online cleaning periods are considered. Therefore, the production bounds of this general case are given by:

$$\bar{\kappa}_{(e,i,t)}^{\min} Y_{(e,i,t)} \leq QE_{(n,e,i,t)} \leq \bar{\kappa}_{(e,i,t)}^{\max} (Y_{(e,i,t)} - \pi_i^{on} V_{(e,i,t)}^{PR}) \quad \forall n \in N, \forall i \in (PR_i \cap CB_i^{on}), e \in E_i, t \in T \quad (4-14)$$

The production unit could produce at most one product resource per time period as modelled by constraints (2-30) and (2-31) of the previous work in Chapter 2.

### 4.5.3 Inventory Tanks for Utilities and Products

The overall system contains a number of resource-dedicated inventory tanks for the storage of utilities and products. Decisions related to inventories depend on each scenario, and thus they are described by second-stage variables through the following set of constraints.

$$B_{(n,e,i,t)}^+ = \sum_{i \in (I_e \cap ZI_i^+)} QE_{(n,e,i,t)} \quad \forall n \in N, e \in E, i \in IT_e, t \in T \quad (4-15)$$

$$\varepsilon_{(e,i,t)}^{+,min} \leq B_{(n,e,i,t)}^+ \leq \varepsilon_{(e,i,t)}^{+,max} \quad \forall n \in N, e \in E, i \in IT_e, t \in T \quad (4-16)$$

$$\begin{aligned} B_{(n,e,i,t)} &= \tilde{\beta}_{(e,i)} + B_{(n,e,i,t)}^+ - B_{(n,e,i,t)}^- & \forall n \in N, e \in E, i \in IT_e, t \in T : t = 1 \\ B_{(n,e,i,t)} &= (1 - \beta_i^{loss}) B_{(n,e,i,t-1)} + B_{(n,e,i,t)}^+ - B_{(n,e,i,t)}^- & \forall n \in N, e \in E, i \in IT_e, t \in T : t > 1 \end{aligned} \quad (4-17)$$

$$\xi_{(e,i)}^{min} \leq B_{(n,e,i,t)} \leq \xi_{(e,i)}^{max} \quad \forall n \in N, e \in E, i \in IT_e, t \in T \quad (4-18)$$

Constraints (4-15) define the total inlet flow ( $B_{(n,e,i,t)}^+$ ) from units  $ZI_i^+$  that are connected to each inventory tank. Constraints (4-16) give the lower and upper bounds on these inlet flows. Resource balances for every inventory tank, scenario and time period are modelled by constraints (4-17), where variables  $B_{(n,e,i,t)}$  indicate the inventory level per scenario, resource and inventory tank at the end of each time period and variables  $B_{(n,e,i,t)}^-$  represent the outlet flow from each inventory tank per scenario. Parameters  $\tilde{\beta}_{(e,i)}$  define the initial inventory for inventory tank at the beginning of the planning horizon (i.e., initial state) and parameters  $\beta_i^{loss}$  give the losses coefficients. Inventory levels bounds are defined by constraints (4-18).

For each time period and scenario, the amount of each utility that leaves its dedicated inventory tank per scenario is equal to the total amount of utility consumed by the associated production units  $ZI_i^-$ . These outlet utility flows are bounded within a lower and upper limit.

$$B_{(n,e,i,t)}^- = \sum_{i' \in (PR_i \cap ZI_i^-)} B_{(n,e,i',t)}^{UT,-} \quad \forall n \in N, e \in E^{UT}, i \in IT_e, t \in T \quad (4-19)$$

$$\varepsilon_{(e,i,t)}^{-,\min} \leq B_{(n,e,i,t)}^- \leq \varepsilon_{(e,i,t)}^{-,\max} \quad \forall n \in N, \forall e \in E^{UT}, i \in IT_e, t \in T \quad (4-20)$$

#### 4.5.4 Demands for Products

For every scenario and time period, demands for products need to be satisfied, according to:

$$NS_{(n,e,t)}^{FP} + \sum_{i \in IT_e} B_{(n,e,i,t)}^- = \zeta_{(n,e,t)} \quad \forall n \in N, e \in E^{PR}, t \in T \quad (4-21)$$

Variables  $NS_{(n,e,t)}^{FP}$  denote the unsatisfied product demand from the internal production system. If the demands for products cannot be met from the internal production system and there are no available external sources for product purchases, these variables represent lost sales of products. A high penalty cost is used in the objective function to avoid satisfying the demands for products from external sources.

#### 4.5.5 Requirements for Utilities (Link between Utility and Production Systems)

Utilities requirements provide the linking constraints between utility and production systems. For each time period and scenario, the utilities needs per production unit  $I_e^{PR}$  consist of: (i) scenario-independent fixed utilities requirements that depend on the operational status of the production unit (first-stage variables); and (ii) scenario-dependent variable utilities requirements that depend on the production level of the production unit (second-stage variables). The utilities balance is then given by the following constraints:

$$NS_{(n,e,i,t)}^{UT} + \sum_{i' \in (IT_e \cap ZI_i^-)} B_{(n,e,i',t)}^{UT,-} = \sum_{e' \in (E^{PR} \cap E_i)} (\alpha_{(i,e,e')} QE_{(n,e',i,t)} + \bar{\alpha}_{(i,e,e')} Y_{(e',i,t)}) \quad \forall n \in N, e \in E^{UT}, i \in I_e^{PR}, t \in T \quad (4-22)$$

Variables  $NS_{(n,e,i,t)}^{UT}$  represent the unsatisfied utility requirements. Similarly to the unsatisfied demand for products, high penalty costs for acquiring utilities from

external sources are introduced in the objective function of the optimisation problem to favor the generation of utilities from the internal utility system.

#### 4.5.6 Objective Function

The optimisation goal is to minimise the total cost of the production and the utility system along with the purchases of products and utilities from external sources. More specifically, the objective function includes: startup and shutdown costs for units, total cleaning costs related to online and offline cleaning tasks of production and utility units that are subject to performance degradation variable, variable and fixed operating costs for units, penalty or purchase costs for acquiring products or utilities from external sources, and total extra energy consumption costs for utility and production units that are subject to performance degradation modelling. The objective function considered in this study is then given by:

$$\min \left[ \begin{aligned}
 & \sum_{t \in T} \sum_{i \in I^{SF}} (\phi_{(i,t)}^S S_{(i,t)} + \phi_{(i,t)}^F F_{(i,t)}) + \sum_{t \in T} \sum_{i \in I^{UT}} (\phi_{(i,t)}^{UT,op-fix} X_{(i,t)}) + \sum_{t \in T} \sum_{i \in PR_i} \sum_{e \in E_i} (\phi_{(e,i,t)}^{PR,op-fix} Y_{(e,i,t)}) \\
 & + \sum_{t \in T} (\sum_{i \in CB_i^{on}} \phi_{(i,t)}^{on} V_{(i,t)} + \sum_{i \in (CB_i^{off} \cup FM_i)} \sum_{q \in Q_i} \phi_{(i,q,t)}^{off} H_{(i,q,t)}) \\
 & + \sum_{n \in N} \sum_{t \in T} \sum_{i \in I^{UT}} (\delta_n^p \phi_{(i,t)}^{UT,op-var} QS_{(n,i,t)}) + \sum_{n \in N} \sum_{t \in T} \sum_{i \in PR_i} \sum_{e \in E_i} (\delta_n^p \phi_{(e,i,t)}^{PR,op-var} QE_{(n,e,i,t)}) \\
 & + \sum_{n \in N} \sum_{t \in T} \sum_{e \in E^{PR}} (\delta_n^p \phi_{(e,t)}^{PR,ex} NS_{(n,e,t)}^{FP}) + \sum_{n \in N} \sum_{t \in T} \sum_{e \in E^{UT}} \sum_{i \in I_{PR}^e} (\delta_n^p \phi_{(e,i,t)}^{UT,ex} NS_{(n,e,i,t)}^{UT}) \\
 & + \sum_{n \in N} \sum_{t \in T} \sum_{i \in CB_i} (\delta_n^p \phi_{(i,t)}^{pw} U_{(n,i,t)})
 \end{aligned} \right] \quad (4-23)$$

In the above expression, the small-letter symbols correspond to the cost coefficients of the corresponding optimisation variables. Probabilities of occurrence for each scenario ( $\delta_n^p$ ) are defined and multiplied with the associated second-stage variables. A detailed definition of each set, parameter, variable of the optimisation framework can be found in the List of Nomenclatures.

#### 4.5.7 Terminal Constraints

Terminal constraints are defined for the last time period of a given optimisation problem as a means of preserving the operability and stability of the system at the end of the planning horizon considered. Terminal constraints are defined for

the minimum inventory levels for utilities and products ( $\lambda_{(e,i)}^B$ ), and the maximum allowable unit performance degradation levels ( $\lambda_i^U$ ) for utility and production units, according to:

$$\begin{aligned} B_{(n,e,i,t)} &\geq \lambda_{(e,i)}^B \xi_{(e,i)}^{\max} && \forall n \in N, e \in E, i \in IT_e, t \in T : t = |T| \\ \delta_i R_{(i,t)} + \delta_i^{cd} D_{(n,i,t)} &\leq \lambda_i^U v_i^{\max} && \forall n \in N, i \in CB_i, t \in T : t = |T| \end{aligned} \quad (4-24)$$

These terminal constraints are applied to any stochastic programming problem solved in this study.

## 4.6 Case Studies

In this part, two case studies are presented for the integrated planning of utility and production systems by employing the proposed stochastic programming approach. Both case studies follow the same plant layout that is displayed in Figure 4-2. The first case study considers a flexible time-window cleaning policy for production units and a condition-based cleaning policy for utility units. The alternative offline cleaning tasks options with respect to duration, cost and cleaning resource requirements are considered. A maximum cleaning resources availability per time period is also considered. It is assumed that the reference operating level for any unit is equal to its maximum operating level. The second case study deals with the reactive planning using the proposed stochastic programming model through a rolling horizon framework. This problem considers a conditioned-based cleaning policy for both utility and production units. The resulting optimisation problems have been written in GAMS 24.8 (Brooke, et al., 1998) and solved with the MIP solver CPLEX 12.7 (ILOG, 2017) in an Intel(R) core(TM) i7-6700CPU@ 3.4 GHz with 8 GB RAM under standard configurations. A 1% optimality gap has been achieved for the first case study after 12 CPU h and a zero optimality gap for all optimisation problems of the second case study.

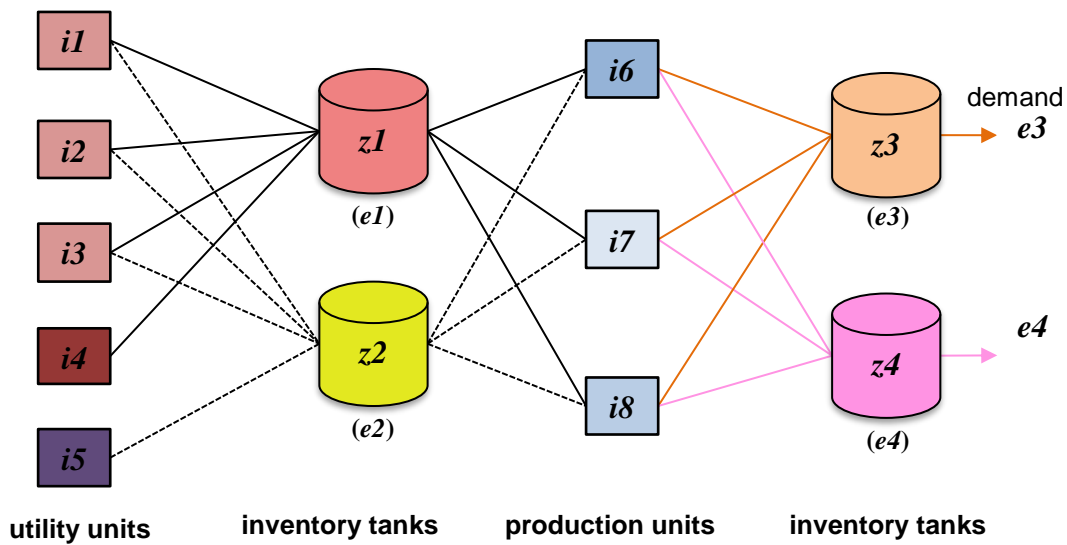


Figure 4-2 Plant layout for both case studies (utility and product flows from left to right)

#### 4.6.1 Case Study 1: Integrated Planning of Utility and Production Systems via Stochastic Programming

In this case study, a combination of cleaning policies for units is studied. More specifically, flexible time-window offline cleaning tasks for production units and conditioned-based cleaning tasks for utility units are considered. The problem has been solved by the proposed two-stage scenario-based stochastic programming model.

##### 4.6.1.1 Description of Case Study 1

The production facility under consideration consists of five utility units ( $i1-i5$ ) and three production units ( $i6-i8$ ). Utility units could produce two utilities ( $e1, e2$ ) which could be either stored in their associated inventory tanks ( $z1, z2$ ) or consumed directly by the production units. Two products ( $e3, e4$ ) could be produced by the production units that can be either stored in their dedicated inventory tanks ( $z3, z4$ ) or meet directly the demands for products. A total planning horizon of 14 days (i.e., 2 weeks), divided in day time periods, is considered. Utility units are subject to online or offline conditioned-based cleaning, while production units are subject to flexible time-window offline cleaning. Earliest and latest starting cleaning times for all production units are on

day 1 and 9. All parameters related to online and offline conditioned-based cleaning for utility units can be found in Table 2-6 in Chapter 2. The only difference is the value for minimum time between two consecutive online cleanings ( $\gamma_i^{on}$ ) that in this case study is considered to be equal to five time periods (i.e., four periods without online cleaning between two online cleanings). All parameters values that fully define the initial state of the overall system are given in Table 4-1. In this case study, initial parameters related to condition-based cleaning tasks (i.e., initial cumulative time of operation  $\tilde{\rho}_i$  and initial state of unit with respect to its last online cleaning  $\tilde{\gamma}_i^{on}$ ) for production units are ignored, since in this problem instance, a condition-based cleaning policy for production units is not considered.

**Table 4-1 Initial state for utility and production units**

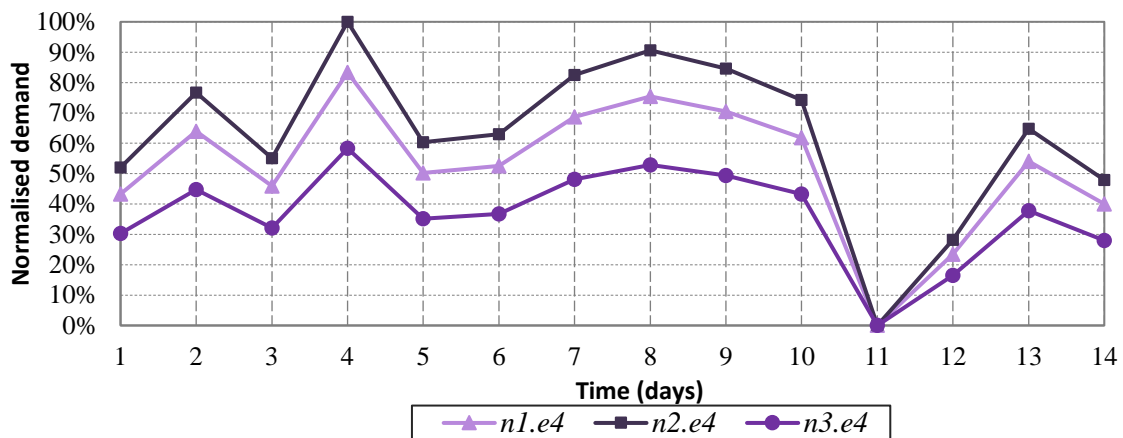
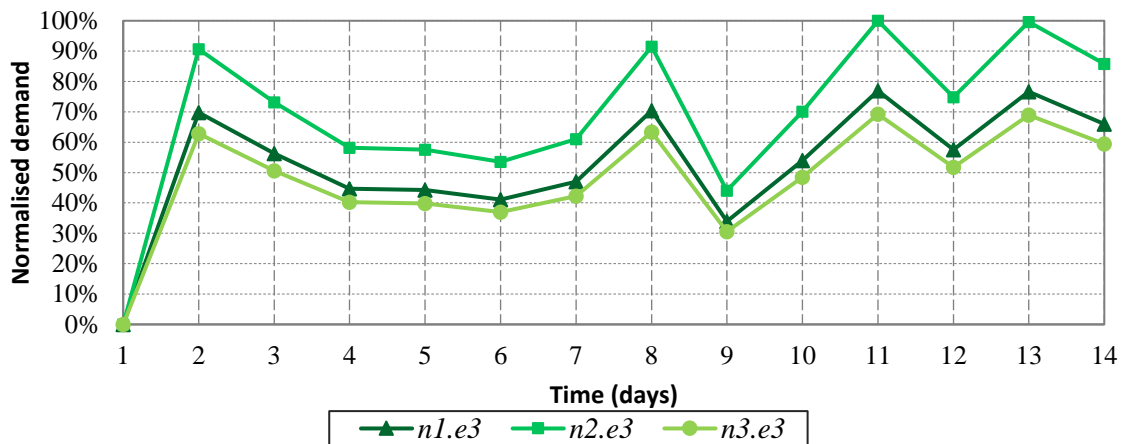
Parameter	<i>i1</i>	<i>i2</i>	<i>i3</i>	<i>i4</i>	<i>i5</i>	<i>i6</i>	<i>i7</i>	<i>i8</i>
$\tilde{\rho}_i$	2	2	7	9	10	6	7	3
$\tilde{\gamma}_i^{on}$	5	14	12	4	17	20	14	14
$\tilde{\omega}_i$	2	16	7	1	7	7	5	18
$\tilde{\psi}_i$	0	0	0	0	0	0	0	0
$\tilde{\rho}_i^{cd}$	2	3	4	3	1	4	3	1
$\tilde{\chi}_i$	1	1	1	1	1	1	1	1
$\tilde{\beta}_{(e1,z1)}$	10	units	Initial inventory for utility <i>e1</i>					
$\tilde{\beta}_{(e2,z2)}$	20	units	Initial inventory for utility <i>e2</i>					
$\tilde{\beta}_{(e3,z3)}$	50	units	Initial inventory for product <i>e3</i>					
$\tilde{\beta}_{(e4,z4)}$	300	units	Initial inventory for product <i>e4</i>					

The following terminal constraints are imposed at the end of the planning horizon. The inventory levels for each inventory tank should be greater or equal to 10% from its corresponding maximum inventory level ( $\xi_{(e,i)}^{max}$ ), and the performance degradation level of any utility unit should be lower or equal to 25% of the

corresponding extra power consumption limit ( $v_i^{max}$ ). Maximum total cleaning resources availability is 12 units for each time period. There are three alternative offline cleaning options ( $q1, q2, q3$ ) that are characterized by different durations, cleaning resources requirements and associated costs. The cleaning duration ( $v_{(i,q)}$ ) for offline cleaning task options  $q1, q2$  and  $q3$  is 3, 4 and 5 days, respectively. The resource requirements ( $\mathcal{G}_{(i,q)}^{off}$ ) for offline cleaning task options  $q1, q2$  and  $q3$  is 6, 4 and 3 cleaning resources, respectively. The resource requirement for online cleanings ( $\mathcal{G}_i^{on}$ ) is 1 cleaning resource. The other main parameters can be found in Table 2-1 to Table 2-5 in Chapter 2.

For the stochastic programming problem, three different scenarios with respect to the demand profiles for products are considered, as displayed in Figure 4-3. More specifically, scenario  $n1$  represents medium demand profiles while scenario  $n2$  and  $n3$  correspond to high and low demand profiles, respectively. The probability of occurrence ( $\delta_n^p$ ) is equal to 30% for scenario  $n1$ , 40% for scenario  $n2$ , and 30% for scenario  $n3$ . Figure 4-3 displays the normalised demand profiles for products by having as a reference the peak demand values of the high-demand scenario  $n2$ . The major assumption in this work is that the three scenarios of demand profiles with respect to low, medium and high demand scenarios are considered the same for all time periods of the proposed two-stage stochastic programming model. Notice that, the number of scenarios considered may not be the most realistic scenarios in a real problem. The most appropriate method to deal with the real problem is multistage stochastic programming model (refer to Section 4.6.1.3). However, these three scenarios of demand profiles are sufficient to show the representation of the two-stage stochastic programming model in order to solve the problem under dynamic demand uncertainty.



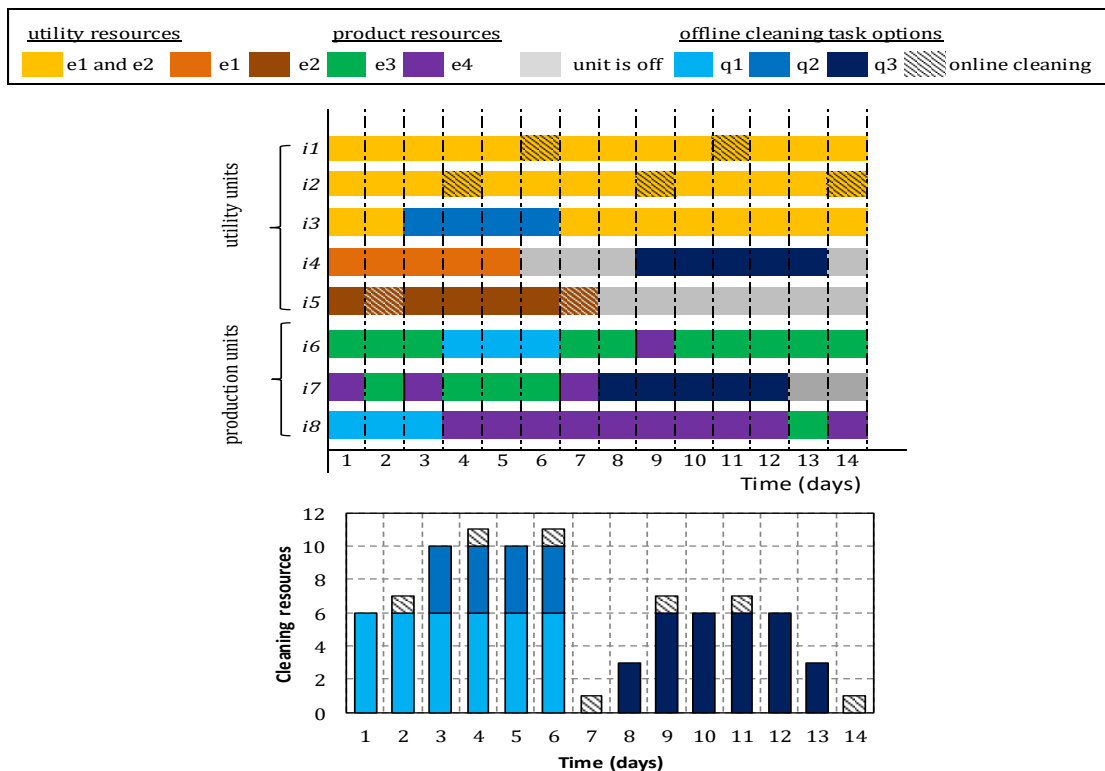


**Figure 4-3 Case Study 1: Normalised demand profiles for products per scenario**

#### 4.6.1.2 Results of Case Study 1

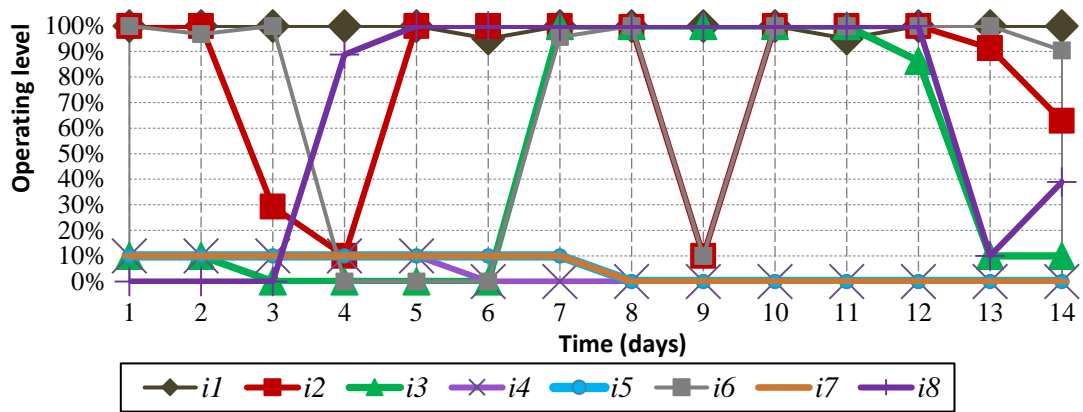
The resulting optimisation model consists of 5,947 equations, 3,514 continuous variables and 923 binary variables. A zero optimality gap was reached after 43,202 CPUs. Figure 4-4 displays the optimal operational and cleaning plan for the production and utility systems. The utilisation profile of cleaning resources is also shown there. Cleaning resources utilisation has its peak in days 4 and 6 where three cleaning tasks take place in parallel. There are no offline cleaning tasks for the utility units  $i1$ ,  $i2$  and  $i5$ , but a number of online cleaning tasks takes place in them. For instance, utility unit  $i1$  undergoes its first online cleaning in day 6 and its second online cleaning in day 11, satisfying the minimum time between two consecutive online cleanings. A similar case is observed in utility

unit  $i_2$  where three online cleanings take place in days 4, 9 and 14. An online cleaning is also observed in day 2 for utility unit  $i_5$ . For utility unit  $i_3$  and  $i_4$  offline cleaning task option  $q_2$  and  $q_3$  start in day 3 and 9, respectively. It is observed that utility unit  $i_4$ , which can only generate utility  $e_1$ , operates only from day 1 to day 5. Although this utility unit does not operate again in the remaining planning horizon, an offline cleaning task takes place in latter periods so as to restore the efficiency of the unit and meet the terminal constraints related to its maximum degradation level at the end of the planning horizon. A similar case is observed for production unit  $i_7$ . Production units  $i_8$  and  $i_6$  undergo offline cleaning tasks  $q_1$  that start in day 1 and 4, respectively. As expected, all offline cleaning tasks for production units start within the predefined earliest and latest starting time (i.e., day 1 to 9). Finally, it is observed that production unit  $i_6$  produces product  $e_3$  and production unit  $i_6$  produces product  $e_4$  in all their operating periods except for one time period.

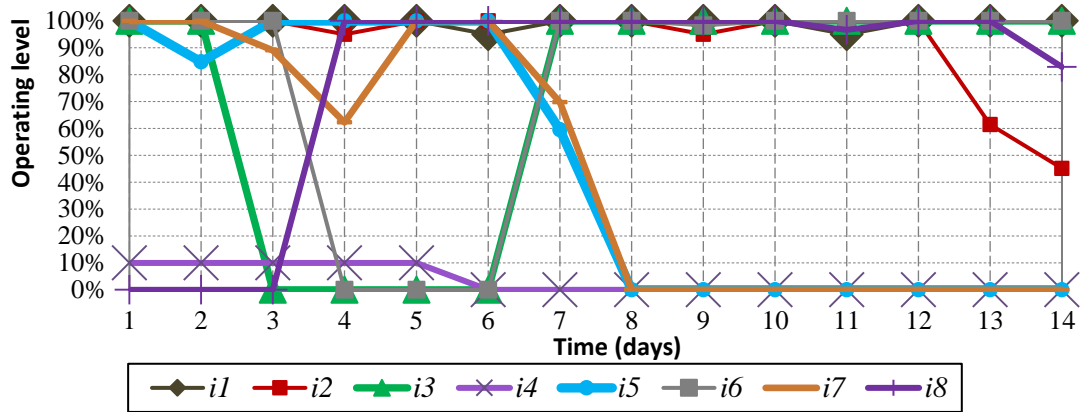


**Figure 4-4 Case Study 1: Optimal operational and cleaning plan for production and utility system and total cleaning resources utilisation profile**

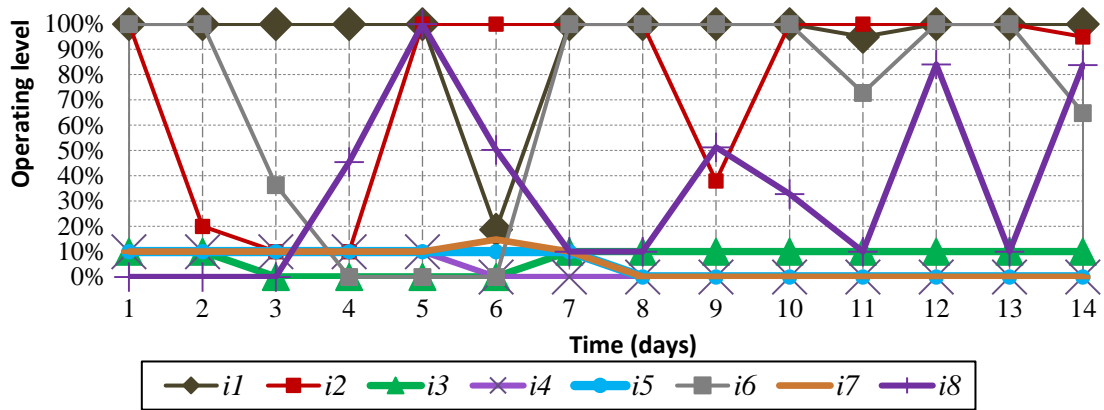
Figure 4-5 displays the normalised operating level profiles for utility and production units for each scenario, having as a reference the maximum operating level of each unit. In the utility system, utility unit *i1* operates at its maximum operating level for all scenarios throughout the planning horizon but in day 6 and 11 due to online cleaning (i.e., due to reduced operating capacity). In general for the scenarios considered, utility unit *i2* operates near or at its maximum operating level for most of the planning horizon but in day 4, 9 and 14 where online cleanings are observed. For all its operating time periods (i.e., excluding cleaning periods), utility unit *i3* operates at its maximum operating level in the high-demand scenario *n2*, but it operates at its minimum operating level in the low-demand scenario *n3*. This has been expected, since lower demand for products would result in lower requirements for utilities. Similar observations can be done for the remaining utility units. In the production system, production unit *i6* operates in its maximum capacity in all its operating periods for all scenarios. Production unit *i8* operates near or at its maximum capacity in most of its operating periods in scenarios *n1* and *n2*, while many operating level fluctuations are observed in the low-demand scenario *n3*. Production unit *i7* operates just half of the planning horizon and its operating level is near or at its minimum in most of its operating periods for scenario *n1*, and near or at its maximum for the high-demand scenario *n2*.



(a) Scenario  $n1$



(b) Scenario  $n2$



(c) Scenario  $n3$

Figure 4-5 Case Study 1: Normalised operating level profiles for utility and production units per scenario

Figure 4-6 displays the normalised total production profiles for each resource (utility or product) per scenario; calculating the aggregated production of each resource from each unit and divide it by the maximum production plant capacity for each resource. As expected, the production peak for resources is observed in the high-demand scenario *n2* followed by those in the medium-demand scenario *n1* and low-demand scenario *n3*. Generally speaking, the production level profiles for utilities *e1* and *e2* follow quite a similar trend at each scenario, mainly due to the three cogeneration utility units. Since production units could produce at most one product at a time, the total production profile for one product follows the opposite trend of that of the other product. In general, production peaks for one product result in production lows for the other. In all scenarios and for any product, its demand in zero or low total production periods is exclusively satisfied by the inventories, since no purchases of products have been reported.

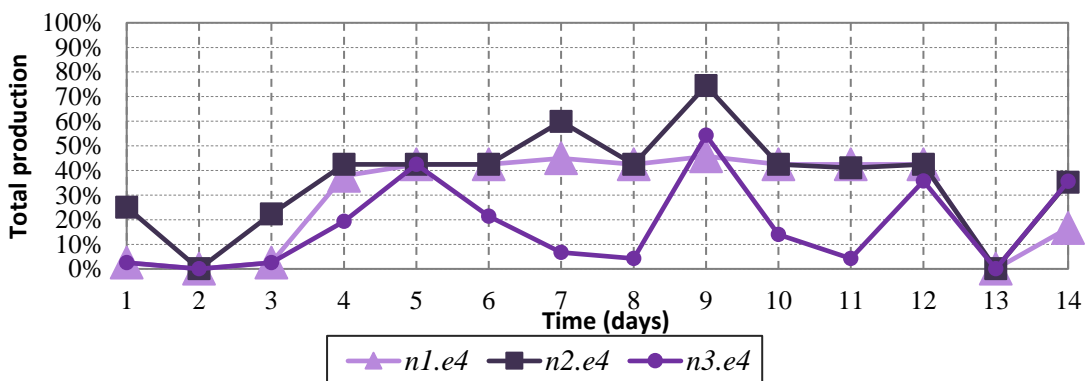
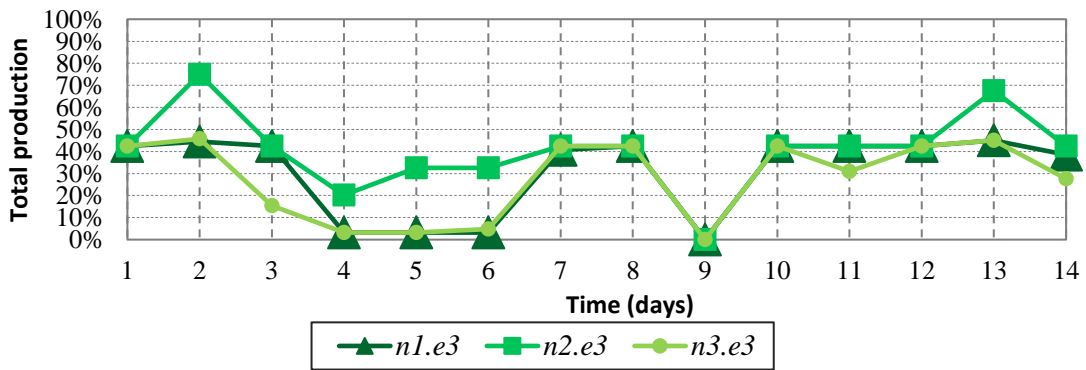
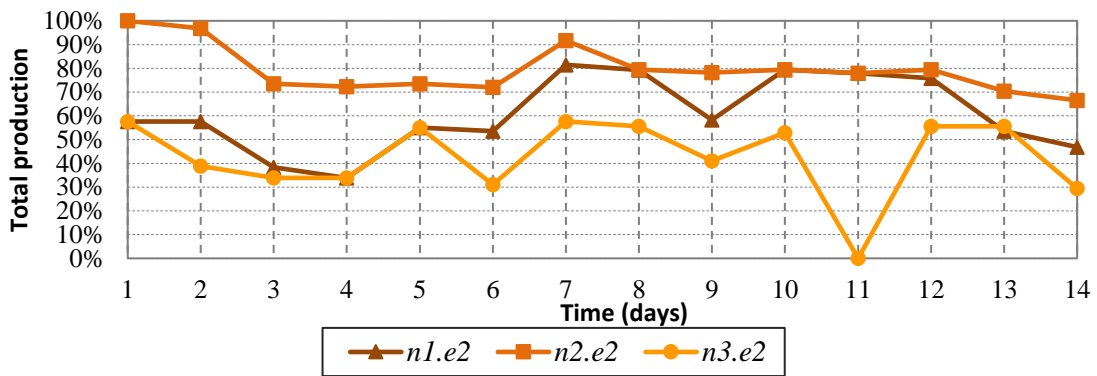
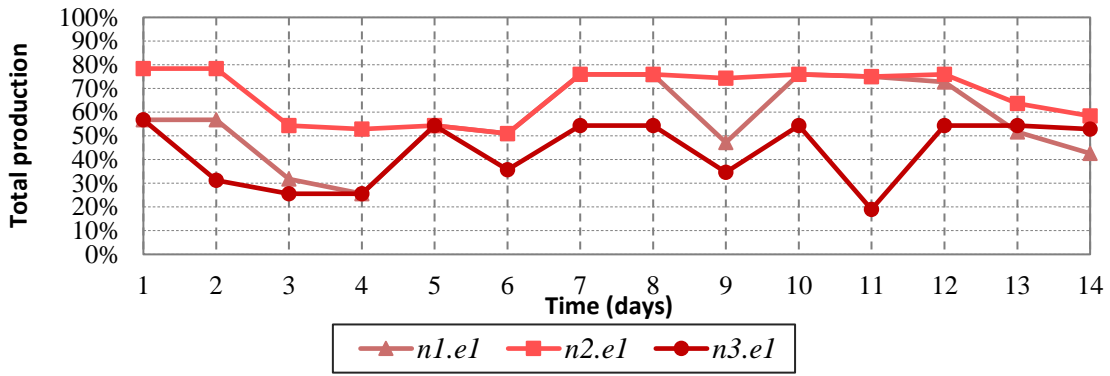


Figure 4-6 Case Study 1: Normalised total production profiles for utilities and products per scenario

Figure 4-7 displays the normalised inventory profiles for utilities and products for each scenario, having as a reference the corresponding maximum inventory level of each inventory tank. For all scenarios at the end of the planning horizon, the inventory levels for utility  $e2$  and products  $e3$  and  $e4$  are 10% of their corresponding maximum inventory levels, which is equal to the lower bound of the imposed terminal constraints. However, the inventory level for utility  $e1$  at the end of the planning horizon is around 80% of its maximum inventory level for all scenarios. This is an indirect result of the operation of the cogeneration units  $i1$  to  $i3$  that satisfy the much higher demand for utility  $e2$  in comparison with that for utility  $e1$ , cogenerating excessive amount of utility  $e1$  that is eventually stored.

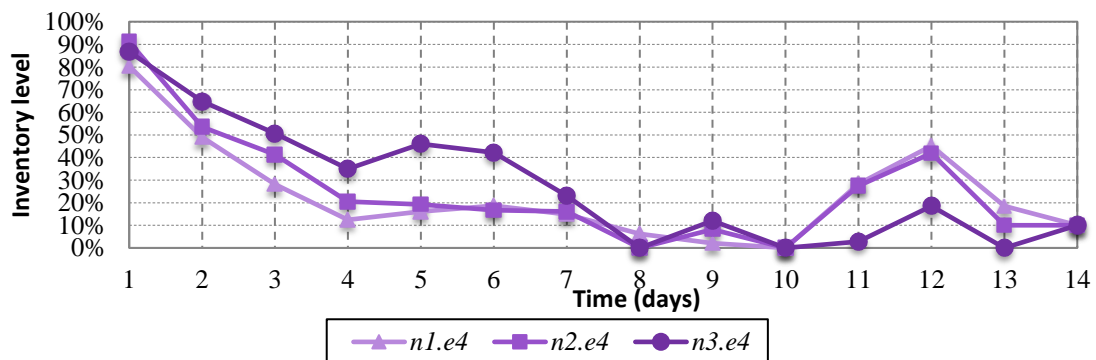
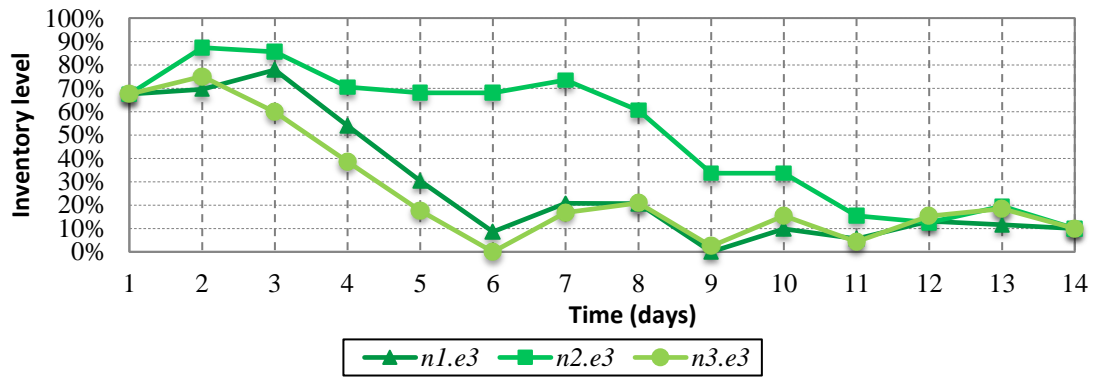
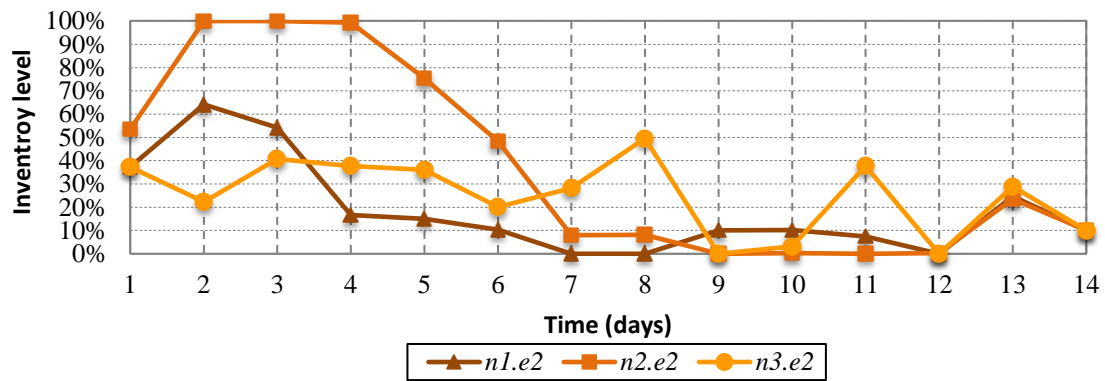
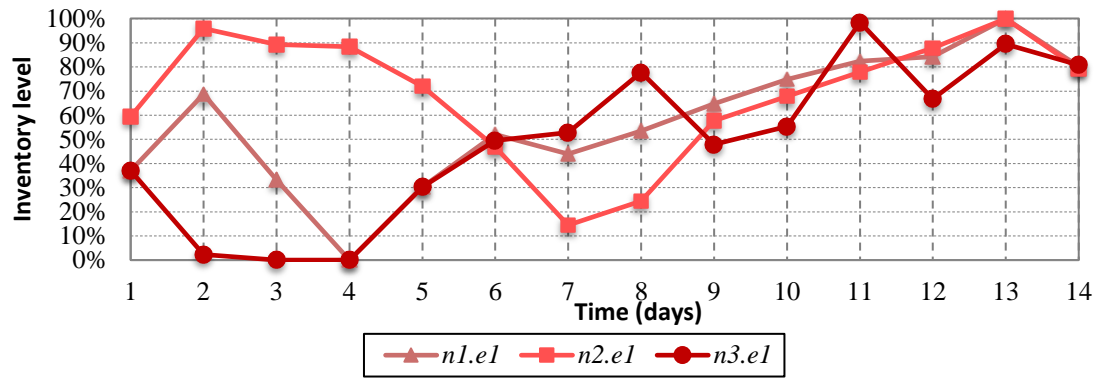
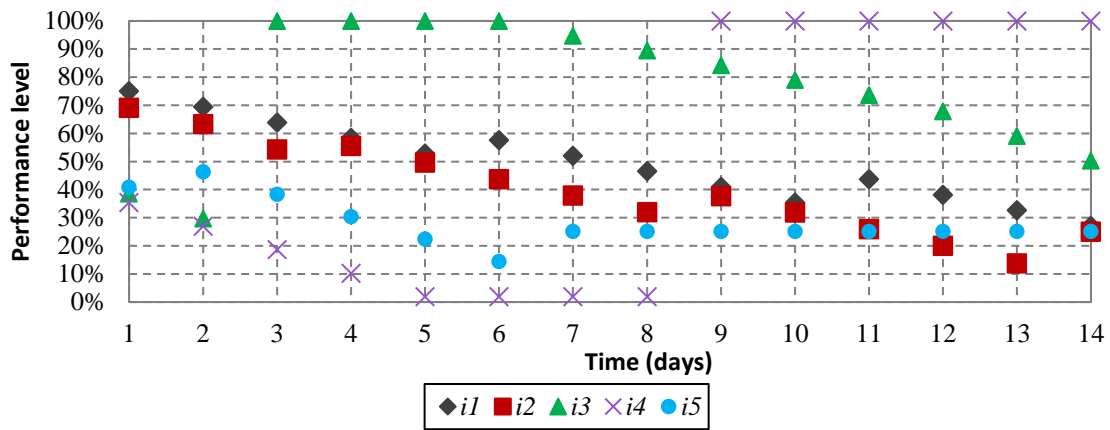


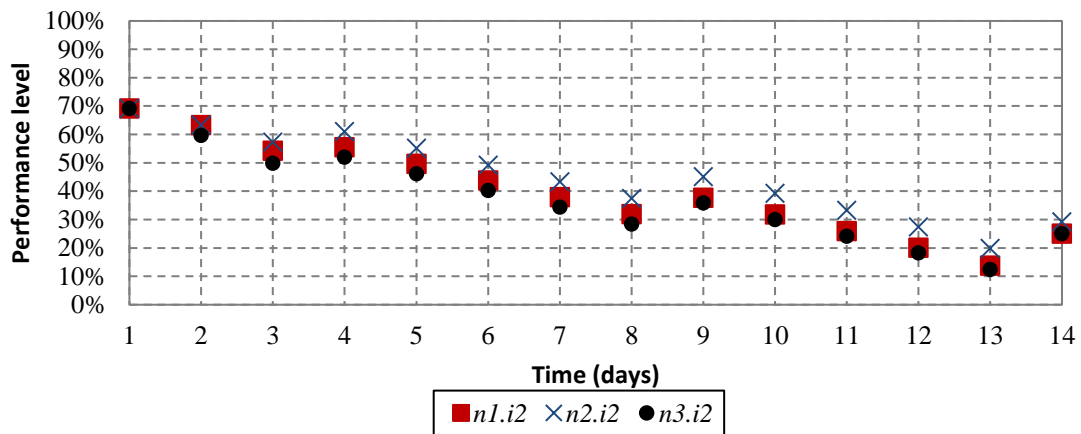
Figure 4-7 Case Study 1: Normalised inventory profiles for utilities and products per scenario





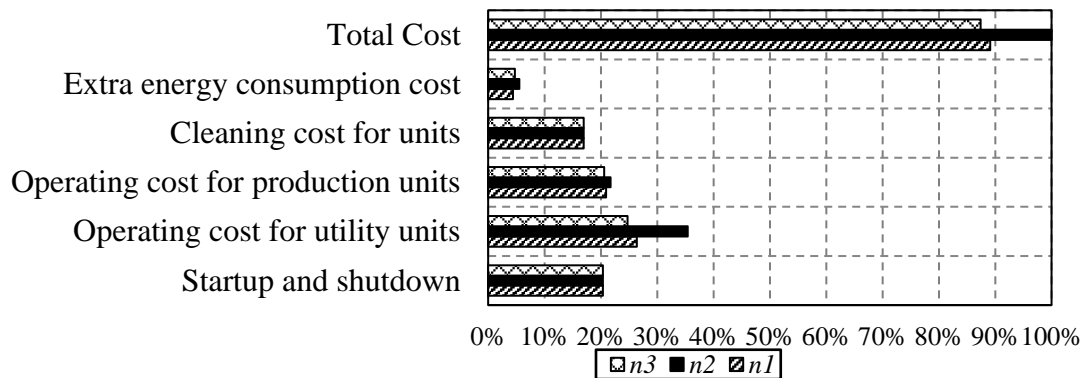
**Figure 4-8 Case Study 1: Performance profiles for utility units for scenario  $n1$**

Figure 4-8 shows the performance level profiles for utility units that are subject to condition-based cleaning for medium-demand scenario  $n1$ . Recall that the performance level of a unit depends on its cumulative time of operation (first-stage variables) and its cumulative operating level deviation (second-stage variables). The performance level profile for other scenarios follows a quite similar trend because the cumulative time of operation is the same for all scenarios (i.e., scenario-independent) and only the cumulative operating level deviation may be different among the scenarios. However, the performance level profiles are almost the same for all scenarios since utility units tend to operate at their maximum load in most their operating periods (see Figure 4-5). Utility units  $i3$  and  $i4$  fully recover their performance though offline cleaning. Also, it can be observed the partial performance recovery of utility units  $i1$ ,  $i2$  and  $i5$  through online cleanings as shown in: (i) day 6 and 11 for utility unit  $i1$ , (ii) day 4, 9 and 14 for utility unit  $i2$ , and (iii) day 2 and 7 for utility unit  $i5$ . At the end of day 14, the performance levels of all operating utility units ( $i1$ ,  $i2$  and  $i3$ ) and non-operating utility units ( $i4$  and  $i5$ ) remain above 25%, satisfying the terminal constraints imposed.



**Figure 4-9 Case Study 1: Performance level profile for utility unit *i2* per scenario**

Figure 4-9 shows the performance level profile for utility unit *i2* per scenario. The highest performance level profile for this unit is observed for the high-demand scenario *n2* which is due to its reduced cumulative operating level deviation since it operates at closer or at its maximum load in most of its operating periods in comparison with the other two scenarios (see Figure 4-6). Recall that the reference operating load for any unit is equal to its maximum operating level.



**Figure 4-10 Case Study 1: Cost breakdown comparison per scenario**

Figure 4-10 shows the cost breakdown comparison among all scenarios. Each cost term for each scenario is divided by the total cost of high-demand scenario *n2* which reports the highest total cost than the other scenarios considered. The costs terms consist of: (i) fixed and varied operating cost for utility units, (ii) fixed and varied operating cost for production units, (iii) extra power consumption cost, (iv) cleaning cost for units, and (v) startup and shutdown cost. The major cost

difference is observed in the operating cost for utility units in scenario *n2* which is 25.4% and 30.2% higher than that in scenario *n1* and scenario *n3*, respectively. In addition, the operating cost for production units in scenario *n2* is 3.7% and 5.3% higher than that in scenario *n1* and *n3*, respectively. Extra energy consumption in scenario *n2* is 20% and 14.1% than that in scenario *n1* and *n3*, respectively. Startup/shutdown and cleaning costs are the same for all scenarios, since they involve only scenario-independent first-stage decision variables. Total cost in high-demand scenario *n2* is 10.9% and 12.6% higher than that in medium-demand scenario *n1* and low-demand scenario *n3*, respectively.

#### 4.6.1.3 Discussion on Problem Size and Computational Performance

The size of the optimisation models depend strongly on the number of time periods considered that affects directly the computational time of the resulting optimisation problems. Table 4-2 shows how the computational time increases dramatically by increasing the number of time intervals, having as a reference Case Study 1 and considering 3 scenarios. In addition, the problem size will grow exponentially with increase number of scenarios because the model is getting bigger with respect to number of constraints and continuous variables, although the number of binary variables remains the same (for the same number of time periods). Notice that, the most appropriate method to solve stochastic problems with increase number of scenarios over multiple time periods is through multi-stage stochastic programming approach whereas the number of scenarios in the first time period increases exponentially with the length of total planning horizon considered. It has also been observed that the assigned scenario probabilities also affect the computational time.

**Table 4-2 Case Study 1: Computational results for different planning horizons**

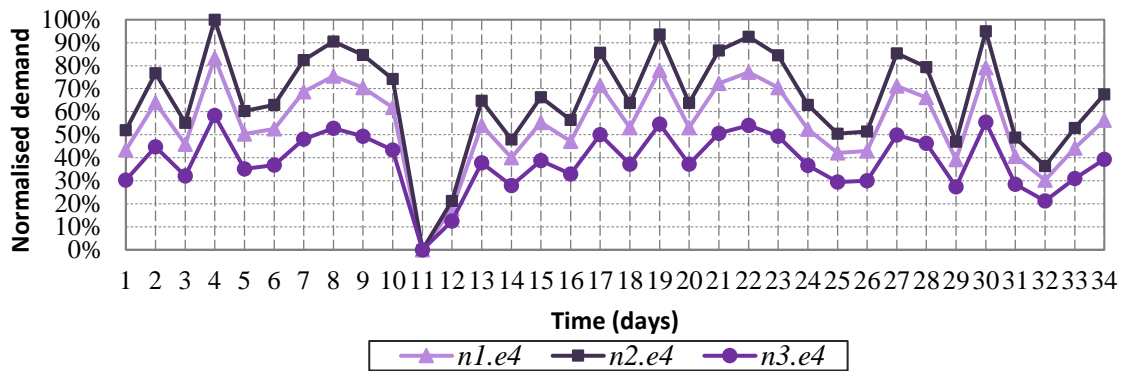
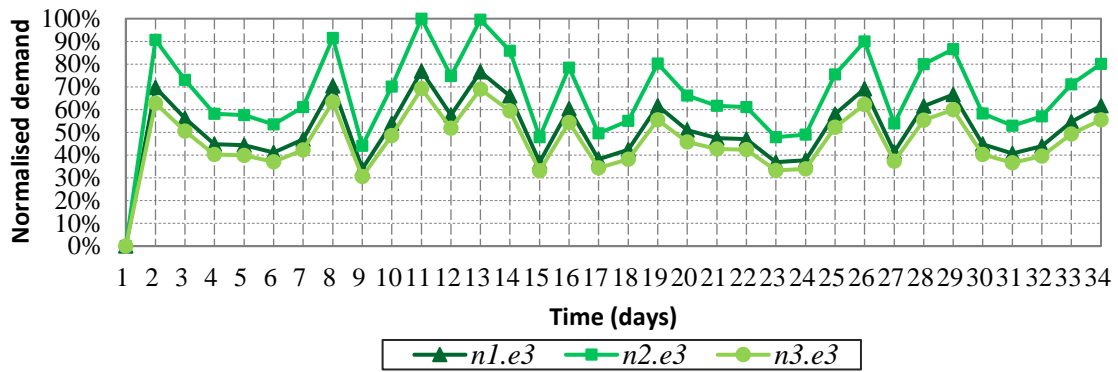
Planning Horizon	Equations	Continous Vars	Binary Vars	CPU s
7 days	3,041	1,807	511	2
14 days	5,947	3,514	923	43,202
21 days	8,838	5,257	1,371	86,400

## **4.6.2 Case Study 2: Integrated Planning of Production and Utility Systems via a Rolling Horizon Stochastic Programming Approach**

This case study presents an application of the rolling horizon stochastic programming approach proposed in this study for a slight variation of the integrated condition-based planning of production and utility systems addressed in the previous case study. A two-stage scenario-based stochastic programming method is followed.

### **4.6.2.1 Description of Case Study 2**

The plant layout as well as main parameters and operational costs are the same as in the previous case study. Terminal constraints, cleaning resources availability and alternative cleaning options are also the same as before. The initial state of the overall system at the beginning of planning horizon is the similar to that of Case Study 1 (see Table 4-1). In contrast to the previous case study, here all production and utility units are subject to condition-based cleaning policies. Also here the minimum time between two consecutive online cleanings in a unit ( $\gamma_i^{on}$ ) is five and six time periods for utility and production units, respectively. A total planning horizon of 28 day time periods is considered here. The demand profiles for products are displayed in Figure 4-11.



**Figure 4-11 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Normalised demand profiles for products per scenario**

For the rolling horizon approach, a prediction horizon equal to seven time periods and a single-period control horizon has been used. A total number of 28 iterations has been solved. For each iteration, the integrated planning problem for the next seven time periods is solved through the two-stage scenario-based stochastic programming model. After each iteration, a planning problem for a new prediction horizon is solved by moving forward the planning horizon by the length of the control horizon considered. Although solutions for all scenarios considered can be obtained, in reality only one can occur after each iteration (under the assumption that exactly one scenario of the ones considered must occur), and this is referred to as an active scenario. Only the solution of the control horizon of the active scenario of the current prediction horizon is applied after each iteration, and therefore the initial state of the overall system for the next prediction horizon is updated according to the solution of the active scenario in the previous iteration. Note that active scenario is the realised demand scenario of the control

horizon of interest that takes into account the solution of first-stage decision variables for all scenarios considered in the previous iteration. In this case study, parameters that need to be updated according to the solution of active scenario are: (i) the level of every inventory tanks; and (ii) the deviation of the operating level per unit. Other parameters that do not depend on active scenario are the solution of the first-stage decision variables such as: (i) the current operating status of each unit; (ii) the startup and shutdown history of units; (iii) the cumulative time of operation per unit; and (iv) the offline and online cleaning history of units. The assumption is that the active scenario of an iteration is not known just before solving the planning problem of the next iteration. Table 4-3 presents the active scenario for each iteration.

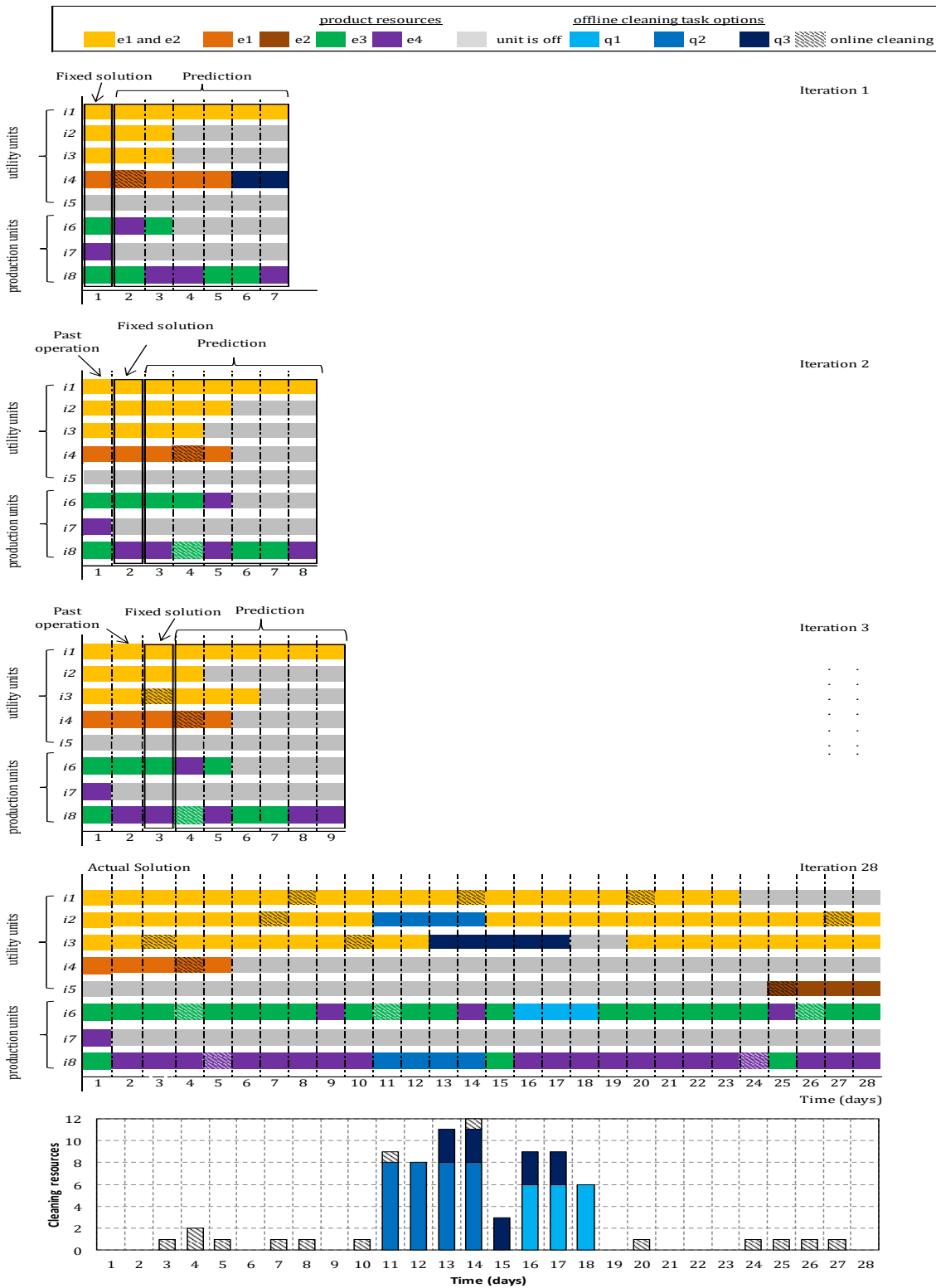
**Table 4-3 Case Study 2: Active scenario per iteration**

Iteration	<u>Active Scenario</u>			Iteration	<u>Active Scenario</u>		
	<i>n1</i>	<i>n2</i>	<i>n3</i>		<i>n1</i>	<i>n2</i>	<i>n3</i>
1			x	15		x	
2	x			16			x
3		x		17		x	
4			x	18		x	
5			x	19	x		
6		x		20		x	
7			x	21		x	
8	x			22			x
9	x			23	x		
10	x			24	x		
11		x		25	x		
12	x			26	x		
13			x	27	x		
14	x			28	x		

#### 4.6.2.2 Results of Case Study 2

On average, each optimisation model consists of 4,020 equations, 2,101 continuous variables and 532 binary variables. The average computational time

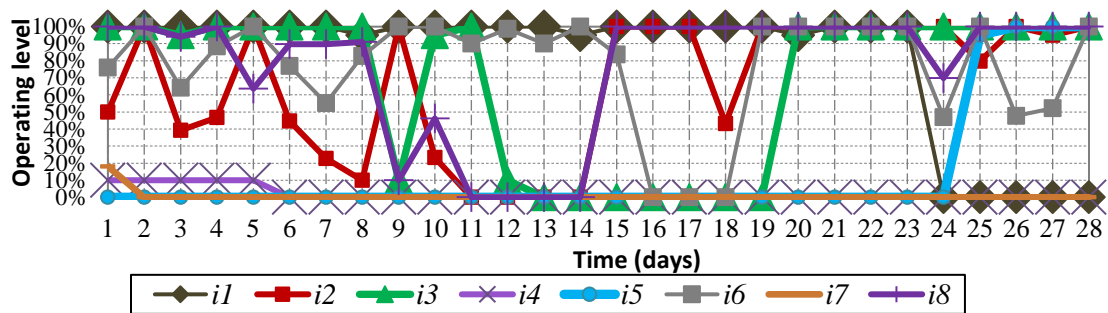
is 3,274 CPUs. Figure 4-12 displays how the final operational and cleaning plan for the 28-day horizon is constructed through the rolling horizon approach. An illustrative example of the first three iterations is presented. The last Gantt chart shows the implemented operational and cleaning plan and the total utilisation profile of cleaning resources for the planning horizon considered. Notice that the implemented Gantt chart is applicable for all scenarios considered, since all binary decisions variables related to the operational and cleaning status of the units are considered as first-stage variables in the stochastic programming model. For the first iteration, a planning problem is solved for time periods 1 to 7 and the solution of the active scenario of the first time period is saved. For the second iteration, a new planning problem for time periods 2 to 8 is solved by updating the initial state according to the active scenario of the first iteration. This receding horizon scheme continues until all 28 iterations are solved. According to Figure 4-12, 4 offline and 14 online cleaning tasks for utility and production units are reported. The maximum total utilisation of cleaning resources is observed in time period 14 where: (i) 8 cleaning resources are needed for two offline cleaning options  $q_2$  in unit  $i_2$ , (ii) 3 cleaning resources for offline cleaning option  $q_3$  at unit  $i_3$  and, (iii) one cleaning resource for the online cleaning of unit  $i_1$ . Simultaneous online cleanings are observed for utility unit  $i_5$  and production unit  $i_6$  in the fourth time period. Utility unit  $i_4$ , which can only produce utility  $e_1$  operates just from day 1 to 5 because cogeneration utility units  $i_1$ ,  $i_2$  and  $i_3$  could not fully satisfy the demand for utility  $e_1$  at this time horizon. Utility unit  $i_5$ , which can produce only utility  $e_2$  operates from day 25 to 28 to satisfy the needs for utility  $e_2$  because utility unit  $i_1$  is closed on these days. In general, production unit  $i_7$  has the highest operational costs in comparison with the other production units. Since the other two production units can satisfy the demand for products for the planning horizon considered, production unit  $i_7$  remains idle throughout the planning horizon but day 1, where it operates due to the minimum run constraint (see Figure 4-12).



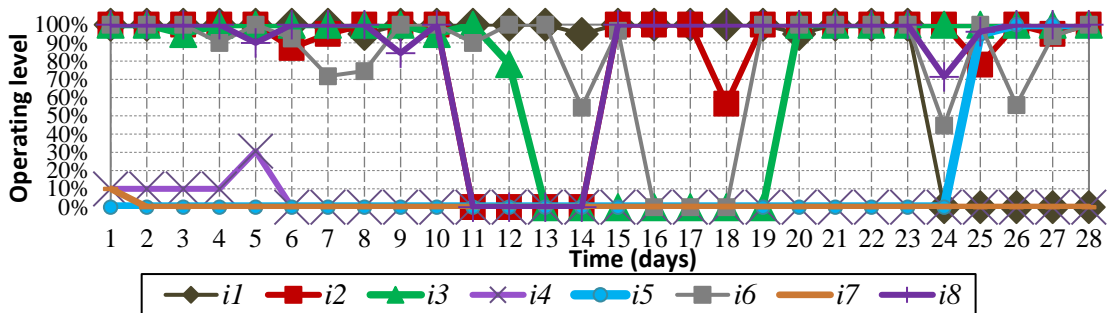
**Figure 4-12 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Plan generation via rolling horizon and total utilisation profile of cleaning resources**



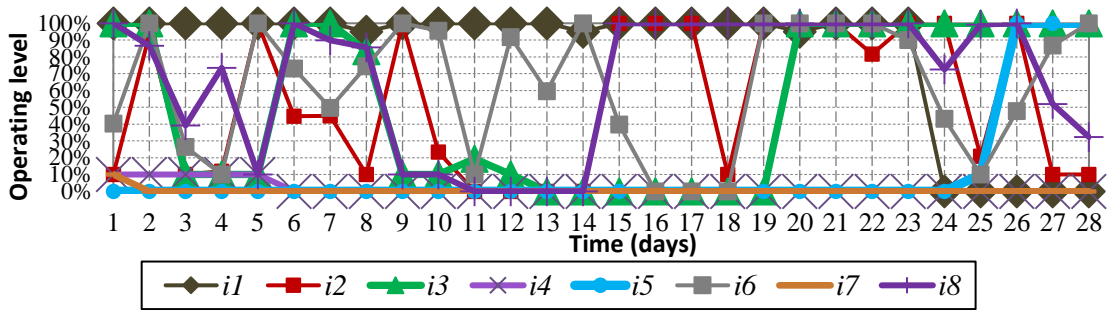
Figure 4-13 shows the normalized operating level profiles per scenario for all units. In the utility system, cogeneration utility unit  $i1$  operates very close or at its maximum operating level until day 23. Cogeneration utility units  $i2$  and  $i3$  operate at varied operating levels satisfying the fluctuations of the utilities requirements. Utility unit  $i4$ , which can generate only utility  $e1$ , operates (for just five time periods) at its minimum operating level in all scenarios, while utility unit  $i5$ , which can only generate utility  $e2$ , operates at its maximum operating level at its limited operating period (from day 25 to 28).



(a) Scenario  $n1$



(b) Scenario  $n2$



(c) Scenario  $n3$

**Figure 4-13 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Normalised operating level profiles for utility and production units per scenario**

Figure 4-14 displays the normalised total production profiles for each utility and product for all scenarios. Similar observations can be made as in the previous case study. Production level trends are observed for utility resources  $e1$  and  $e2$  for all considered scenarios because there are three cogeneration utility units (i.e.,  $i1$ ,  $i2$  and  $i3$ ). In general, the highest production profiles for both utilities throughout the planning horizon is observed in high-demand scenario  $n2$ . The production peak for product  $e3$  is observed in day 15 for all considered scenarios, because two production units (i.e.,  $i6$  and  $i8$ ) operating at their high operating levels produce this product at in this time period. A similar observation can be made for product resource  $e4$  in day 9.

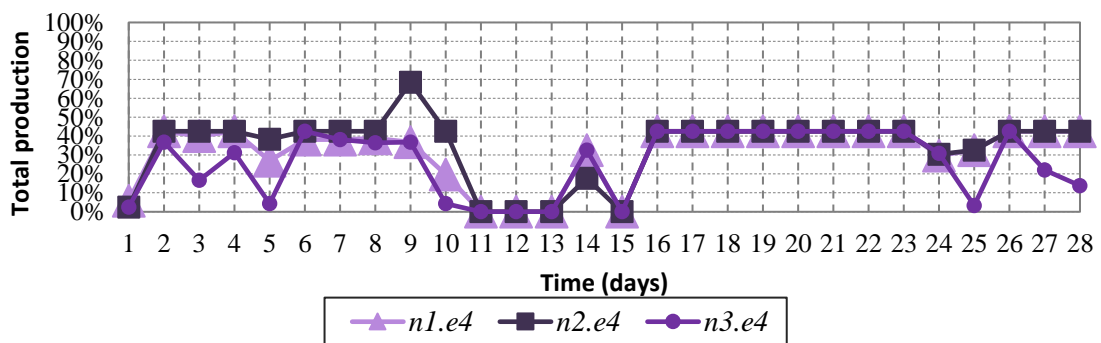
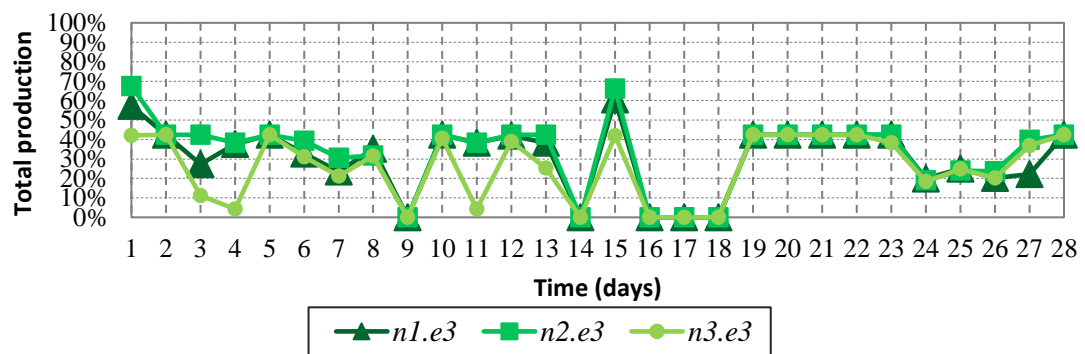
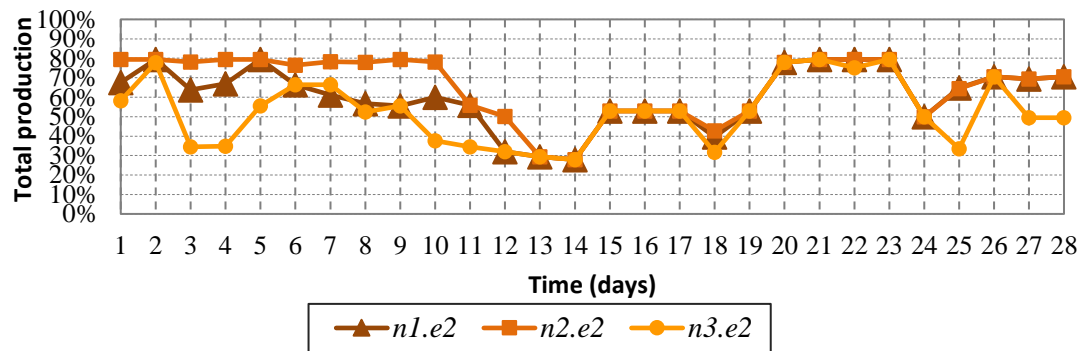
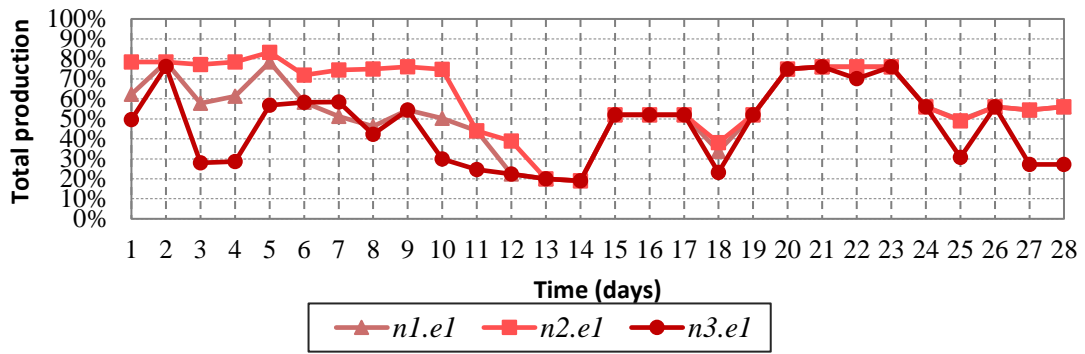


Figure 4-14 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Normalised total production profiles for utilities and products per scenario

Figure 4-15 displays the normalized inventory profiles for utilities and products, having as reference the corresponding maximum inventory level of each inventory tank. Low inventory levels for utility  $e1$  is observed for all scenarios from day 13 to 15, because of the simultaneous multiple cleaning tasks in the cogeneration units at those periods (see Figure 4-12). High inventory levels for utility  $e2$  is reported for all scenarios from day 11 to 18 due to low utility demand at these time periods, because of the offline cleanings taking place in some production units (see Figure 4-12). For all scenarios, low inventory levels for product  $e3$  are observed from day 16 to 18 because no production of product  $e3$  takes place then. The inventory level for product  $e4$  reduces from day 11 to 15 due to the very limited production of product  $e4$  occurs in this time period (see Figure 4-12 and Figure 4-14). In general, inventory levels for both products in the low-demand scenario  $n3$  are slightly higher than those of other scenarios. It is important to recall that all inventory levels are subject to terminal constraints (i.e., higher than 10% of the maximum capacity of its inventory tank). For some scenarios, the inventory level for utility  $e2$  in day 28 is below 10%. It should be clear that this is not a violation of the terminal constraint. The solution of day 28 (i.e., iteration 28) is derived by solving the planning problem for a prediction horizon from day 28 to day 34, and for that planning problem the terminal constraint is satisfied in the last time period of the prediction horizon considered (i.e, day 34 and not day 28).

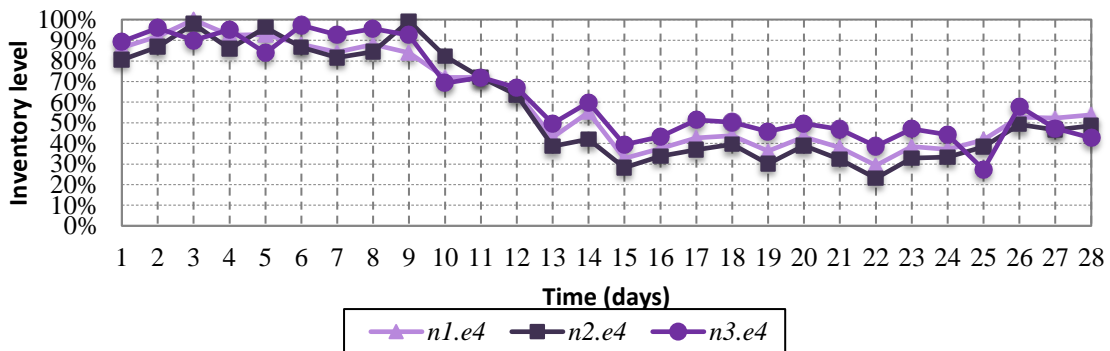
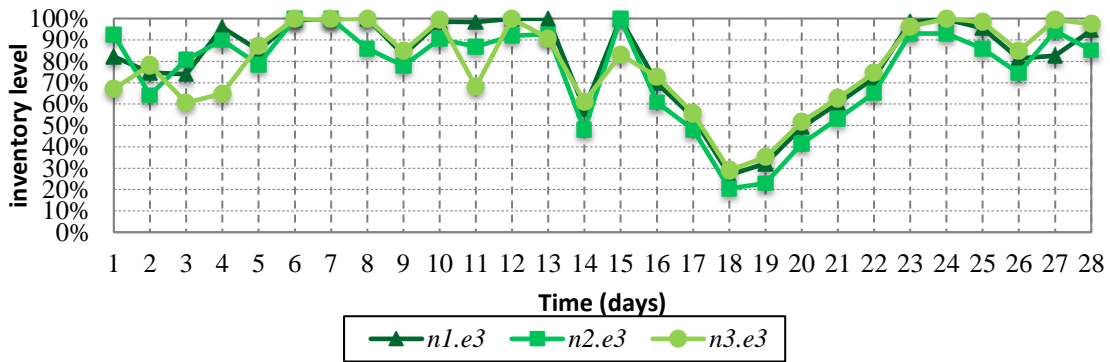
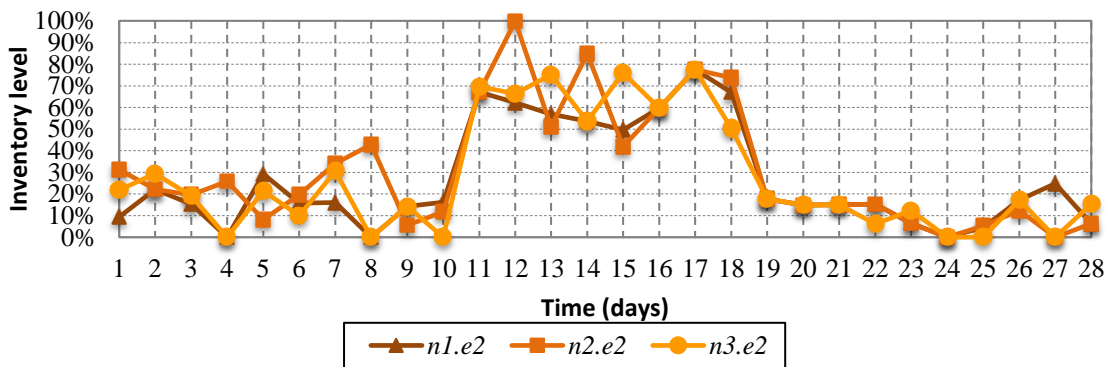
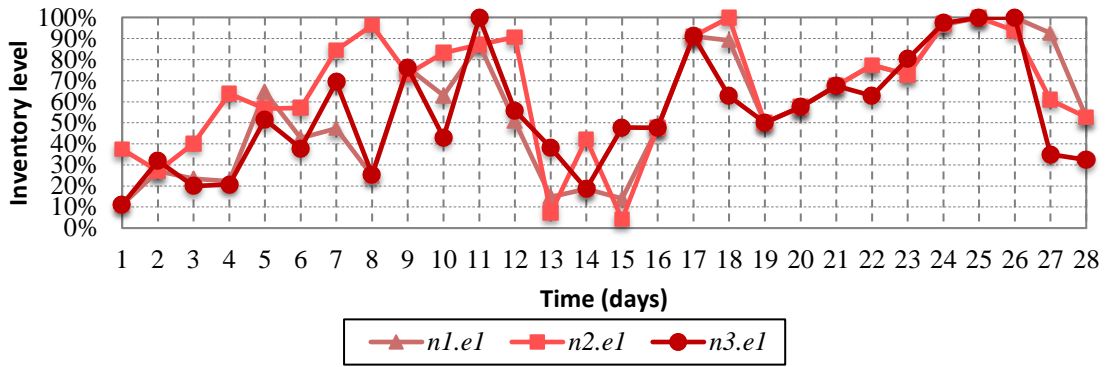
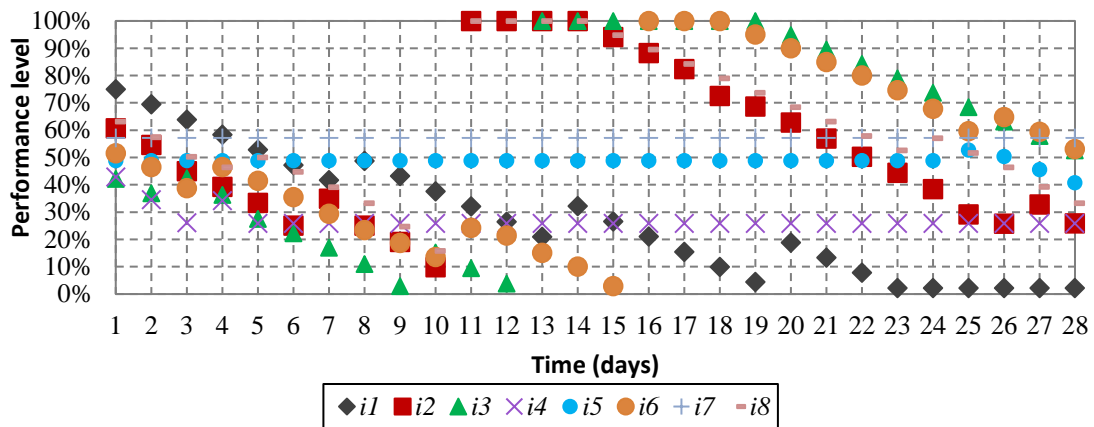
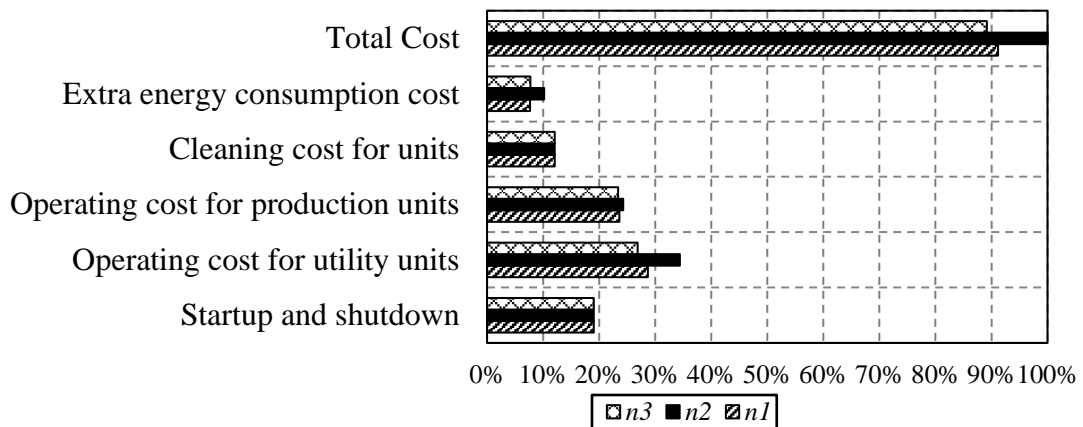


Figure 4-15 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Normalised inventory profiles for utilities and products per scenario



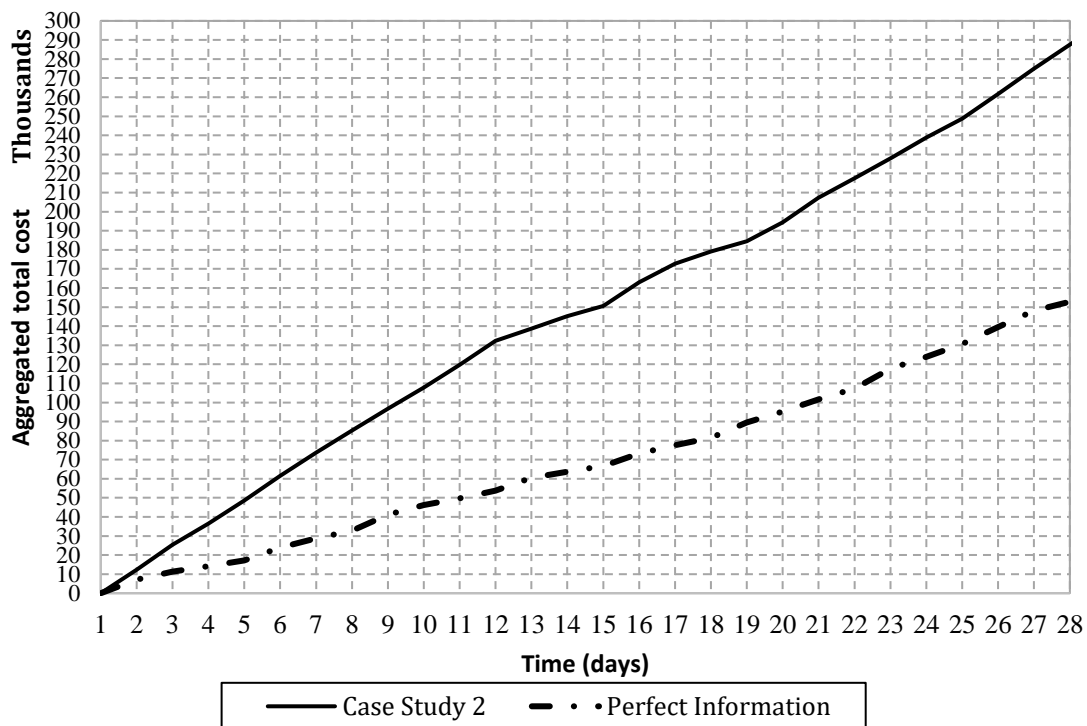
**Figure 4-16 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Performance level profiles for utility and production units for scenario  $n3$**

The performance level profiles for utility and production units for scenario  $n3$  are displayed in Figure 4-16. Recall that the performance level of a unit depends on its cumulative time of operation and its cumulative operating levels deviation. Similar to Case Study 1, performance level profiles for the other scenarios are about the same. The performance of some utility units (i.e.,  $i2$  and  $i3$ ) and production units (i.e.,  $i6$  and  $i8$ ) is fully recovered once an offline cleaning occurs. It is also shown how a unit partially recovers its performance through online cleaning. For instance, unit  $i1$  partially recovers its performance when online cleanings occur in day 8, 14 and 20. Note that the performance level of utility unit  $i2$  declines in a slightly varied rate from day 17 to 18 and 24 to 25 due to its operating level deviation from its maximum capacity (see Figure 4-13). Recall unit performance levels are subject to terminal constraints (i.e., higher than 25% of the maximum performance of each unit). The performance level of utility unit  $i1$  in day 28 is below 25%, but this is not a violation of the terminal constraint as already discuss before for the inventory level terminal constraints.



**Figure 4-17 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Cost term comparison for each scenario**

According to Figure 4-17 that shows a comparative cost breakdown among scenarios, total cost in high-demand scenario *n2* is 8.9% and 10.9% higher than that in medium-demand scenario *n1* and low-demand scenario *n3*, respectively. Similarly to the previous case study, the major cost difference is observed in the operating cost for utility units in scenario *n2* which is 16.6% and 21.9% higher than that in scenario *n1* and scenario *n3*, respectively. Extra energy consumption in scenario *n2* is 24.6% and 24.0% than that in scenario *n1* and *n3*, respectively. Finally, the operating cost for production units in scenario *n2* is 2.7% and 3.7% higher than that in scenario *n1* and *n3*, respectively.



**Figure 4-18 Case Study 2 - Rolling Horizon Stochastic Programming Approach: Aggregated total cost comparison**

Figure 4-18 displays the aggregated total cost for rolling horizon stochastic programming approach and perfect information solution. The active scenario in the perfect information solution changes for every time period in the current prediction horizon. The results show that the total cost of the case study 2 is 48% higher than that of the perfect information solution. The perfect information solution is the best solution one could obtain. However, in practice this solution is impossible to be found due to uncertainty in the demand for products. It should be clear that the obtained solution could be improved, if the accuracy to forecast uncertainty is improved and the length of prediction horizon increases.

## 4.7 Conclusions

A hybrid reactive/proactive optimisation framework for the operational and resource-constrained condition-based cleaning planning problem of integrated production and utility systems under uncertainty has been presented in this work. The proposed approach relies on a two-stage scenario-based stochastic



programming model for the problem in question, applied within a rolling horizon scheme. Improved unit performance degradation and recovery models based on cumulative operating level deviations and cumulative operating times have been presented. Terminal constraints for minimum inventory levels for utilities and products as well as maximum unit performance degradation levels have been introduced too. Although in the case studies, demand uncertainty has been only considered, the proposed method can deal with several other types of uncertainty (e.g., price fluctuations). The proposed approach provides significant support to decision makers, since it can obtain the detailed optimal operational and cleaning plan of the utility and production system as a whole, and reporting operating levels profiles for units, performance level profiles for units, total production profiles for resources, inventory profiles, and total costs. The case studies presented highlighted the particular features and showed the applicability of the proposed approach as an effective means of dealing with the integrated planning problem considered under dynamic environments.

## 5 A GENERAL OPTIMISATION FRAMEWORK FOR THE DESIGN AND PLANNING OF ENERGY SUPPLY CHAIN NETWORKS: TECHNO-ECONOMIC AND ENVIRONMENTAL ANALYSIS <sup>d</sup>

### 5.1 Abstract

A general spatial optimisation framework that relies on the use of a modified state-task network representation for design and planning problems in material and energy supply chain networks is presented. In brief, the proposed optimisation framework considers for the tasks and states of the network: (i) the optimal selection and sizing of conversion, transfer and storage technologies, (ii) the capacity expansion for each technology over time, (iii) the inventory level for storable states, (iv) the quantity of states converted or transferred through tasks, and (v) the optimal energy mix. Several variations of an illustrative design and planning problem of a mixed material and energy supply chain network have been solved effectively to study the trade-off between costs and emissions levels and different emission regulation policies. A sensitivity analysis study with respect to alternative emissions caps and a multi-objective optimisation example considering the conflicting objectives of total cost and emissions are also presented. The case studies showed that a more efficient way for emissions reductions is through regulation and emissions caps rather than increased emissions costs (i.e., 3.3% emissions reductions). Overall, the proposed optimisation framework could be used to integrate various types of material and energy supply chain operations using a unified modelling representation towards the more efficient management of such interdependent networks under techno-economic and environmental aspects.

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<sup>d</sup> Zulkafli, N.I. and Kopanos, G.M. (2018b) 'A general optimization framework for the design and planning of energy supply chain networks: Techno-economic and environmental analysis', *Chemical Engineering Research and Design*, 131, pp. 214–233.

## 5.2 Introduction

Modern energy networks have been continuously improving towards reducing their environmental footprint by introducing low-carbon technologies, improving energy efficiency of the overall system and securing energy resources for their long-term sustainable operation. The main challenge in energy systems lies on how to systematically improve energy supply and demand side by considering environmental sustainability and efficient economic performances. Environmental sustainability may involve integration of clean technologies into the conventional energy system to tackle the effects of greenhouse gas emission. This integration should result in solutions that are characterised by both reduced environmental footprint and improved economical and operational performance targets. Towards these targets, an integrated energy supply chain network should consider the capacity expansion of the involved technologies and the optimal generation and flow of resources within the whole network to achieve a cost-effective energy supply chain network design, with reduced emissions levels while ensuring the demand satisfaction of the end users.

In recent years, energy systems engineering has been emerged as an excellent means of providing systematic approaches that could quantify different levels of complexity of such systems (i.e., technology, plant, energy supply chain network). More specifically, energy systems engineering provides a solid methodological scientific framework to arrive at integrated solutions to complex energy systems problems, by adopting a holistic systems-based approach for optimisation, simulation and control problems of energy supply chains networks. Energy systems engineering approaches have been presented for subjects related to design and control modelling (Diangelakis and Pistikopoulos, 2017), integrated operational and maintenance planning (Zulkafli and Kopanos, 2016), and low-carbon energy systems (Corbetta et al., 2016). The abovementioned works studied and developed state-of-the-art methodologies and tools for energy systems planning, design, operation and control from various levels in process plant to supply chain and system-wide levels as covered in a recently published book (Kopanos, Liu and Georgiadis, 2017).

The focus of this study is on material and energy supply chain networks that consist of several types of interdependent and interconnected technologies that could be located in different geographical regions and perform various process, such as exploitation of energy resources from natural reservoirs, transformation of resources into intermediate and final products, transfer of energy or material resources to end users of other downstream technologies of the overall network. A general modelling representation is proposed in this study for the unified modelling of material-based and energy-based supply chains. Based on the proposed modelling representation, a general optimisation framework is developed that could be used for the modelling of several types of energy supply chains design and planning problems (e.g., oil and gas industries, power industries, and renewable energy industries etc.). This general modelling representation is proposed as a means for the integrated management of material and energy supply chain networks within a single optimisation framework, and constitutes the main contribution of this study.

This chapter is structured as follows. The literature review is presented in Section 5.3. In Section 5.4, the proposed modelling approach for the design and planning of energy supply chains is described. The problem statement of the study is formally defined in Section 5.5. The proposed optimisation framework is then presented in Section 5.6, followed by the description and discussion of the results of the case studies in Section 5.7. Finally, some concluding remarks are provided in Section 5.8.

### **5.3 Literature Review**

A good number of energy systems engineering research works on the subject can be found in the open literature. For example, Kim et al. (2011) studied the optimal design of biomass supply chain networks for biofuels. Fernandes et al. (2013) proposed mixed integer linear programming model for the strategic design and planning of petroleum supply chains. Hasan et al. (2014) presented a mathematical model for the optimisation of nationwide, regional, and statewide carbon capture, utilisation, and sequestration supply chain networks. Koltsaklis

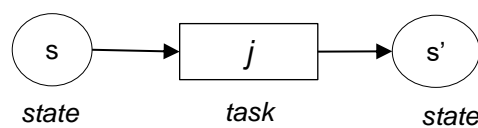
et al. (2014) developed an optimisation model for the design and operational planning of energy networks based on combined heat and power units. Guerra et al. (2016) presented optimisation frameworks for the integrate design and planning of water networks and shale gas supply chains. In addition, Arredondo-Ramírez et al. (2016) presented optimal infrastructure planning approaches for shale gas supply chain networks. Ng and Maravelias (2017) proposed an optimisation model for the design of biofuel supply chains with variable regional depot and biorefinery locations. Gao and You (2017) developed a modelling framework and computational algorithm for hedging against uncertainty in sustainable supply chain design using life cycle optimisation. Calderón et al. (2017) presented an optimisation framework for the design of synthetic natural gas supply chains.

For material-based supply chain networks, Grossmann (2005) discussed the need for enterprise-wide approaches for the integrated management of supply, production and transportation activities. Shah (2005) and Papageorgiou (2009) provided excellent reviews on the design and planning considering uncertainty, business and sustainability aspects. Most of the suggestions and conclusions drawn in these works apply to the energy supply chain case. Although there is a large number of works in the open literature that cope with different types of material or energy supply chains, there is a lack of a unified modelling representation for dealing with combined material and energy supply chain networks under an integrated optimisation framework.

#### **5.4 Proposed Modelling Approach: Energy State Task Network (E-STN)**

In this work, a general representation for modelling operations in energy supply chains inspired by the State Task Network (STN) representation for chemical processes (Kondili, Pantelides and Sargent, 1993) is presented. The STN is a directed graph that consists of three key elements: (i) state nodes that represent the feeds as well as intermediate and final products, (ii) task nodes that stand for the process operations which transform material from one or more input states into one or more output states, and (iii) arcs that link state and task nodes

indicating the flow of materials. In this representation, state and task nodes are denoted by circles and rectangles, respectively (see Figure 5-1). The salient characteristic of the STN representation is that distinguishes the process operations from the resources that may be used to execute them, and therefore provides a means for describing very general process recipes. The STN representation has been broadly used in process scheduling problems with some applications to material-based supply chain networks (Lainez et al., 2009) and biomass supply chains (Pérez-Fortes et al., 2012).



**Figure 5-1 Typical State Task Network (STN) representation**

In the context of energy supply chain networks, the definition of states and tasks of the original STN representation should be modified so as to be able to model the set of operations performed in such environments. That way, a unified modelling framework for the operations in energy supply chains is developed. In addition, the modelling representation is based on a spatial approach that divides the overall geographical region of interest (e.g., a country) into a finite number of zones. The formal definition of the states and nodes as well as the types of technology considered in the proposed Energy supply chain STN (E-STN) representation follows.

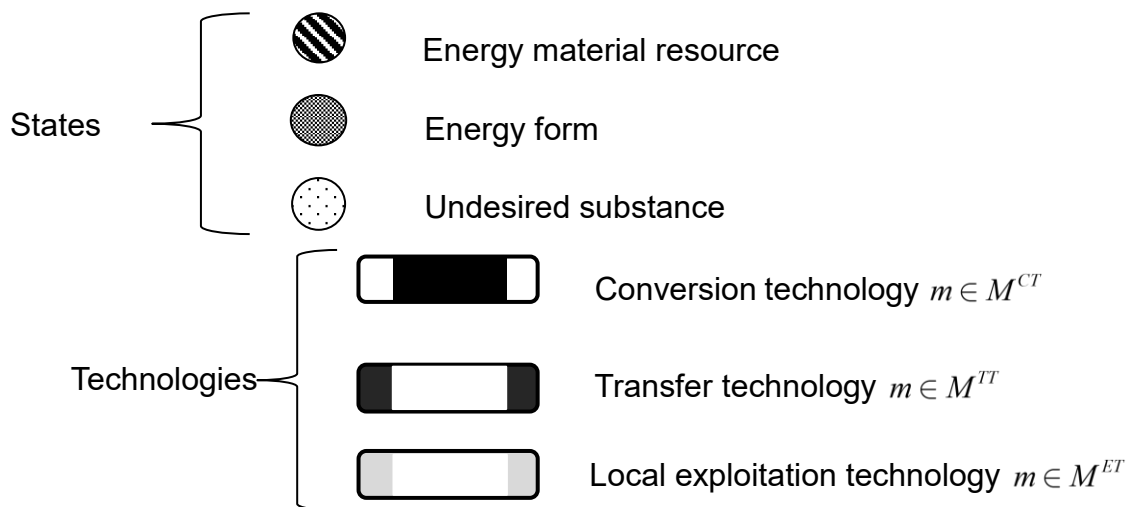
#### **5.4.1 Definition of States in Energy Supply Chain Operations**

In this work, the classification of state nodes into energy material resources, energy forms, and undesired substances is presented; as shown in Figure 5-2.

- Energy material resources states represent material resources, non-renewable primary or secondary energy material resources, "renewable" biomass materials (wood, energy crops, forest or agricultural residues, municipal solid waste, etc.) and biofuels (e.g., bioethanol, biodiesel).

Primary energy material resources include fossil fuels (such as coal, petroleum, natural gas) and nuclear fuels (such as Plutonium-239 and Uranium-235). Secondary energy material resources comprise chemical fuels such as diesel, ethanol, propane, butane, gasoline and hydrogen.

- Energy forms states represent secondary energy, such as electrical energy and heat as well as primary renewable energy such as solar, wind, geothermal energy and energy from water (excluding biomass and biofuels). In contrast to energy material resources states, energy form states are not tangible.
- Undesired substances states represent unwanted elements that can contaminate or have a harm effect in the natural environment. Contaminants and pollutants of different forms (i.e., solid particles, liquid droplets, or gases) as well as greenhouse gases, such as carbon dioxide and nitrogen oxide, are typically the main undesired by-product substances in energy supply chain networks.



**Figure 5-2 E-STN representation: states and technologies**

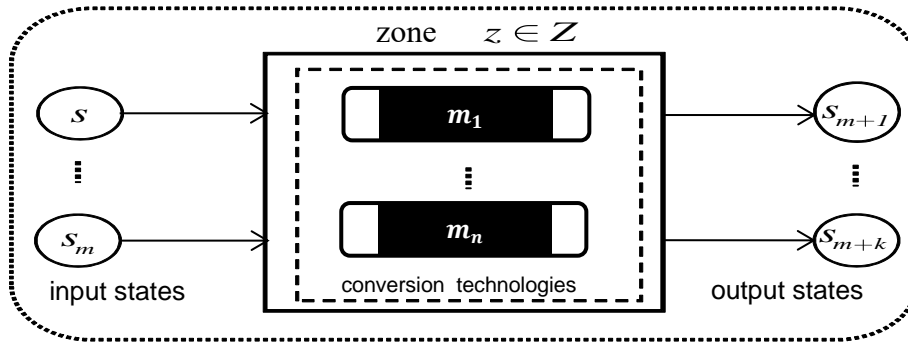
### 5.4.2 Definition of Tasks in Energy Supply Chain Operations

The task nodes are categorised into conversion tasks, transfer tasks and local exploitation tasks, as described below.

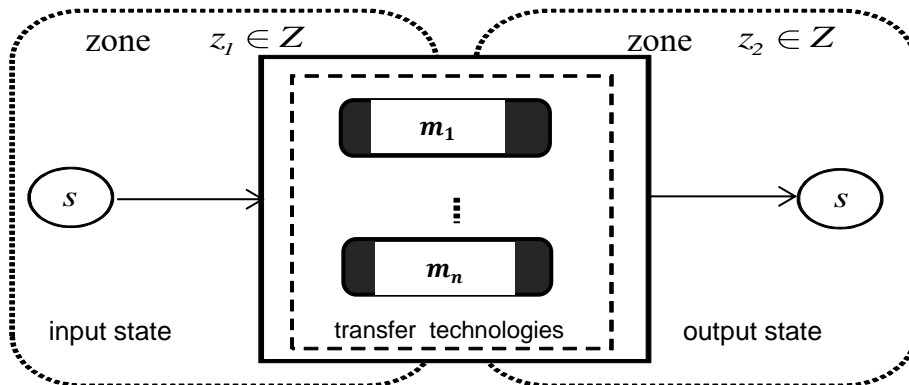
- Conversion tasks represent tasks that can transform a set of any type of states into a different set of states, as shown in Figure 5-3(a). For instance, a conversion task (e.g., combustion) may transform energy material resources states (e.g., coal) into energy forms states (e.g., electricity and heat) and undesired substances states (carbon dioxide, etc.). A conversion task (e.g., photovoltaic effect) could transform energy forms (e.g., solar energy) into other energy forms (e.g., electricity). In addition, a conversion task (e.g., fermentation) may transform energy material resources states (e.g., sugarcane, wheat or corn) into other material resources states (e.g., bioethanol). Even a conversion task (e.g., scrubbing for carbon capture) may transform undesired substances states (e.g., flue gas) into other undesired substances states (e.g., carbon dioxide). Many other combinations of input and output states in conversion tasks exist.
- Transfer tasks represent tasks that can transfer a given state (of any type) from one zone to another. As Figure 5-3(b) depicts, the output state of the transfer task is the same with the input state; although the quantity may be different (e.g., due to losses). Once again, this definition of transfer tasks is very general. For instance, a transfer task using a proper transfer technology (e.g., railroad, ship, trucks) may transport an energy or material resource state (e.g., coal). An energy form (e.g., electricity) could be transferred by a transfer task through a transfer technology (e.g., power grid) is also considered. This approach also allows the representation of transfer operations for undesired substances states. Depending on the nature, the type and other particular characteristics of the state different transfer technology options may exist. Notice that not all states (e.g., solar or wind energy) can be transferred.
- Local exploitation tasks represent tasks that can exploit locally available (in given capacity) energy or material resources states, referred to as raw materials states. These tasks are considered as imaginary transfer tasks and technologies as shown in Figure 5-3(c). Local exploitation tasks may involve minerals or fossil fuel sources (e.g., extraction of coal or crude oil)



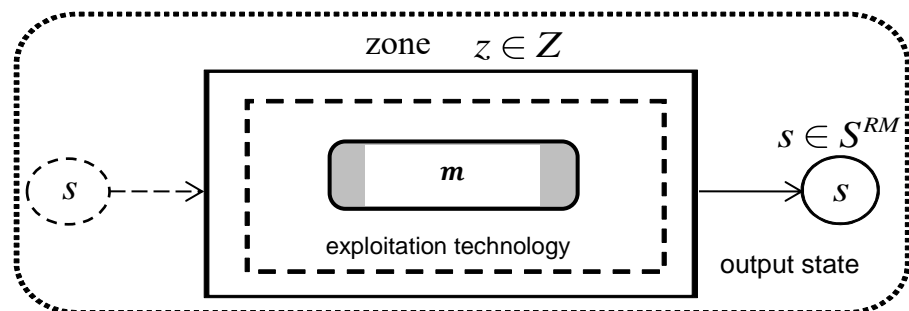
or exploitation of available renewable energy sources (e.g., solar radiation, wind, etc.). Notice that transfer of available locally states from one zone to another could also take place through transfer tasks as long as the state is transferable.



(a) Conversion task



(b) Transfer task



(c) Local exploitation task

**Figure 5-3 E-STN representation: tasks**

### 5.4.3 Definition of Types of Technologies in Energy Supply Chain Operations

The following main types of technologies are considered: conversion, transfer, and local exploitation, as displayed in Figure 5-2.

- Conversion technologies could perform conversion tasks. The definition of conversion technologies may include energy generation technologies from combustion (power plants, combined heat and power), electrochemical (e.g., fuel cells) or nuclear (e.g., fusion or fission) conversion to biomass pretreatment units and technologies for energy generation from primary renewables (e.g., photovoltaics, wind turbines, etc.). Technologies that transform a set of states to another set of states are considered as conversion technologies. An example of such technologies is the reformer of a fuel cell system that extracts hydrogen (output state) from natural gas (input state). Technologies (e.g., scrubbers) used to capture undesired substances states are also considered as conversion technologies.
- Transfer technologies could perform transfer tasks. The definition of transfer technologies used here is very broad. For example, transfer technology could be any type of transportation modes (e.g., railroad, ship, road), pipelines networks (e.g., for natural gas or transfer of hot water or steam) and electrical grids.
- Local exploitation technologies could perform local exploitation tasks. For example, the local exploitation technology could be of any type of exploitation mode such as crude oil extraction, natural gas extraction, coal exploitation, wind energy exploitation through wind turbines, solar energy exploitation through photovoltaic panels, etc.

The storage technologies that could store any type of storable states (e.g., storage tanks to store energy material resources states, heat buffer tanks or batteries to store energy form states) are also defined. Storage technologies are not displayed in the E-STN, since storage is not defined as a task.

## 5.5 Problem Statement

This study focuses on the modelling representation of material and energy supply chains under design, planning and economic constraints. The problem under study considers a geographical region that has a number of material and energy sources and is characterised by varied material and energy needs throughout a given long-term time horizon. The supply chains problem is formally defined in term of the following items:

- A given planning horizon divided into a number of equally-length time periods  $t \in T$ .
- A set of zones  $z \in Z$  that is divided into internal zones ( $z \in Z^{in}$ ) and external zones ( $z \in Z^{ex}$ ).
- A set of energy forms and energy material resources states  $s \in S$  that are classified by raw material states ( $s \in S^{RM}$ ) with maximum amount of available raw material states  $\omega_{(z,s,t)}$ , product states ( $s \in S^{FP}$ ) with known demand profiles  $\zeta_{(z,s,t)}$ , storable states ( $s \in S^B$ ) with minimum  $\beta_{(z,s,t)}^{\min}$  and maximum  $\beta_{(z,s,t)}^{\max}$  inventory levels and disposable states ( $s \in S^D$ ).
- A set of tasks  $j \in J$  that could perform by a number of technologies  $m \in M$  and can consume or produce states. These tasks are categorised to local exploitation tasks ( $j \in J_s^{RM}$ ), input and output tasks ( $j \in J_s^-$  and  $j \in J_s^+$ ), and transfer tasks ( $j \in J_s^{TT}$ ).
- A number of technologies  $m \in M$  that are categorised into local exploitation technology ( $m \in M^{ET}$ ), conversion technology ( $m \in M^{CT}$ ), transfer technology ( $m \in M^{TT}$ ) and, storage technology ( $m \in M^{ST}$ ). For each conversion, local exploitation and storage technology, the lower  $\gamma_{(z,m,t)}^{\min}$  and upper  $\gamma_{(z,m,t)}^{\max}$  bound of the capacity expansion are defined. Similarly, the lower  $\gamma_{(z,z',t)}^{T,\min}$  and upper  $\gamma_{(z,z',t)}^{T,\max}$  bound of the capacity expansion for transfer technology is also defined.

- For every conversion, local exploitation and transfer technology, the lower and upper bound of available capacity are given as  $\alpha_{(z,z,i,m,t)}^{\min}$  and  $\alpha_{(z,z,i,m,t)}^{\max}$ , respectively.
- Given investment cost to establish the respective technology  $\varepsilon_{(z,m,t)}^{EST}$  and investment cost to expand the capacity of its technology  $\varepsilon_{(z,m,t)}^{ICS}$ .
- Given fixed operating cost  $\delta_{(z,m,t)}$ , raw materials cost  $\psi_{(z,s,i,m,t)}^E$ , production cost  $\pi_{(z,s,i,m,t)}$ , inventory cost  $\lambda_{(z,s,t)}$ , transfer cost  $\varphi_{(z',z,s,i,m,t)}$  and disposable cost  $\lambda_{(z,s,t)}^D$ .

The additional considerations of the problem under study are the following: (i) the demands for products states should be fully satisfied; and (ii) the states can be disposed per time period especially the undesired substances states, the disposal of energy material resources and energy form states can be avoided by putting high values of disposable cost.

For every time period, the key decisions to be made by the optimisation model are:

- the selection of technology for each task;
- the amount of capacity expansion and total installed capacity for each technology;
- the inventory level for storable states in its respective storage technology;
- the quantity of states converted or transferred through tasks that can be performed by its respective technology.

The objective is to minimise the cost of the energy supply chain design and planning that includes:

- fixed assets costs that include investment cost to establish and expand conversion, local exploitation and storage technologies;
- fixed transfer cost to establish and expand transfer technology;
- fixed operating cost on the total installed capacity of the conversion technologies;

- variable costs which include production, inventory and transfer cost; and
- disposable cost for the release of states to the environment (e.g., emissions cost).

## 5.6 Optimisation Framework

In this section, a mixed integer programming model based on the proposed E-STN representation is presented for the design and planning problem of energy supply chains. The whole set of constraints of the proposed mathematical model is categorised into: (i) design constraints, (ii) design-planning linking constraints, (iii) planning constraints, (iv) economics equations, and (v) the objective function. The description of the proposed model follows.

### 5.6.1 Design Constraints

#### 5.6.1.1 Establishment of Capacity Expansion for Technologies

In order to model the installation status of the energy supply chains operations, the following set of binary variables is introduced:

$$WC_{(z,m,t)} = \begin{cases} 1 & \text{if conversion or local exploitation technology } m \text{ is established in zone } z \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$YC_{(z,m,t)} = \begin{cases} 1 & \text{if capacity of conversion or local exploitation technology } m \text{ begins installing in zone } z \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$WS_{(z,s,m,t)} = \begin{cases} 1 & \text{if storage technology } m \text{ for state } s \text{ is established in zone } z \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$YS_{(z,s,m,t)} = \begin{cases} 1 & \text{if capacity of storage technology } m \text{ for state } s \text{ begins installing in zone } z \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

$$YT_{(z,z',m,t)} = \begin{cases} 1 & \text{if capacity of transfer technology } m \text{ begins installing in zone } z \text{ in time period } t, \\ 0 & \text{otherwise.} \end{cases}$$

Constraints (5-1) ensure that the establishment of each conversion or local exploitation ( $m \in M_z^{CE}$ ) and storage technology ( $m \in M_{(s,z)}^{ST}$ ) could take place at most once in any internal zone ( $z \in Z^in$ ) throughout the time horizon considered. The establishment of a technology represents first-time investment decisions often related to fundamental infrastructure construction. Constraints (5-2) and (5-3) link the binary variables that represent the establishment and the capacity

expansion of technologies. A technology establishment could only take place if and only if a capacity expansion occurs at the same time period, as defined by constraints (5-2), and at the same time there has been no establishment in the previous time periods, as modelled by constraints (5-3).

$$\begin{aligned} \sum_{t \in T} WC_{(z,m,t)} &\leq 1 \quad \forall z \in Z^{in}, m \in M_z^{CE} \\ \sum_{t \in T} WS_{(z,s,m,t)} &\leq 1 \quad \forall z \in Z^{in}, s \in S, m \in M_{(s,z)}^{ST} \end{aligned} \quad (5-1)$$

$$\begin{aligned} WC_{(z,m,t)} &\leq Y_{(z,j,t)} \quad \forall z \in Z^{in}, m \in M_z^{CE}, t \in T \\ WS_{(z,s,m,t)} &\leq YS_{(z,s,m,t)} \quad \forall z \in Z^{in}, s \in S, m \in M_{(s,z)}^{ST}, t \in T \end{aligned} \quad (5-2)$$

$$\begin{aligned} WC_{(z,m,t)} &\geq YC_{(z,j,m,t)} - \sum_{t' < t} WC_{(z,m,t')} \quad \forall z \in Z^{in}, j \in J_z^{CE}, t \in T \\ WS_{(z,s,m,t)} &\geq YS_{(z,s,m,t)} - \sum_{t' < t} WS_{(z,s,m,t')} \quad \forall z \in Z^{in}, s \in S_z^B, j \in J_{(s,z)}^B, t \in T \end{aligned} \quad (5-3)$$

### 5.6.1.2 Total Capacity Installed and Expansion for Technologies

For each zone and time period, the total installed capacity for each conversion or local exploitation technology ( $FC_{(z,m,t)}$ ), storage technology ( $FC_{(z,s,m,t)}^{ST}$ ), and transfer technology ( $FC_{(z,z',m,t)}^{TT}$ ) are modelled by the following set of constraints:

$$\begin{aligned} FC_{(z,m,t)} &= \varphi_{(z,m)} + FC_{(z,m,t-1)} + EC_{(z,m,t)} \quad \forall z \in Z^{in}, m \in M_z^{CE}, t \in T : t = 1 \\ FC_{(z,m,t)} &= FC_{(z,m,t-1)} + EC_{(z,m,t)} \quad \forall z \in Z^{in}, m \in M_z^{CE}, t \in T : t > 1 \end{aligned} \quad (5-4)$$

$$\begin{aligned} FC_{(z,s,m,t)}^{ST} &= \varphi_{(z,s,m)}^{ST} + FC_{(z,s,m,t-1)}^{ST} + EC_{(z,s,m,t)}^{ST} \quad \forall z \in Z^{in}, s \in S_z^B, m \in M_{(s,z)}^{ST}, t \in T : t = 1 \\ FC_{(z,s,m,t)}^{ST} &= FC_{(z,s,m,t-1)}^{ST} + EC_{(z,s,m,t)}^{ST} \quad \forall z \in Z^{in}, s \in S_z^B, m \in M_{(s,z)}^{ST}, t \in T : t > 1 \end{aligned} \quad (5-5)$$

$$\begin{aligned} FC_{(z,z',m,t)}^{TT} &= \varphi_{(z,z',m)}^{TT} + EC_{(z,z',m,t)}^{TT} \quad \forall z \in Z^{in}, z' \in Z_{z'}^T, j \in J_{(z,z')}^T, t \in T : t = 1 \\ FC_{(z,z',m,t)}^{TT} &= FC_{(z,z',m,t-1)}^{TT} + EC_{(z,z',m,t)}^{TT} \quad \forall z \in Z^{in}, z' \in Z_{z'}^T, j \in J_{(z,z')}^T, t \in T : t > 1 \end{aligned} \quad (5-6)$$

Parameters  $\varphi_{(z,m)}$ ,  $\varphi_{(z,s,m)}^{ST}$  and  $\varphi_{(z,z',m)}^{TT}$  stand for the initial installed capacity of each technology per zone.

For each technology and zone, variables  $EC_{(z,m,t)}$ ,  $EC_{(z,s,m,t)}^{ST}$  and  $EC_{(z,z',m,t)}^{TT}$  represent the corresponding capacity expansion taking place per time period, as defined by:

$$\begin{aligned} \gamma_{(z,m,t)}^{\min} YC_{(z,m,t-\mu_{(z,m,t)}^{CE})} &\leq EC_{(z,m,t)} \leq \gamma_{(z,m,t)}^{\max} YC_{(z,m,t-\mu_{(z,m,t)}^{CE})} & \forall z \in Z^{in}, m \in M_z^{CE}, t \in T \\ \gamma_{(z,m,t)}^{\min} YS_{(z,s,m,t-\mu_{(z,m,t)}^{ST})} &\leq EC_{(z,s,m,t)} \leq \gamma_{(z,m,t)}^{\max} YS_{(z,s,m,t-\mu_{(z,m,t)}^{ST})} & \forall z \in Z^{in}, s \in S_z^B, m \in M_{(s,z)}^{ST}, t \in T \end{aligned} \quad (5-7)$$

$$\gamma_{(z,z',t)}^{T,\min} YT_{(z,z',j,t-\mu_{(z,z',m,t)}^{TT})} \leq EC_{(z,z',j,t)}^{TT} \leq \gamma_{(z,z',t)}^{T,\max} YT_{(z,z',j,t-\mu_{(z,z',m,t)}^{TT})} \quad \forall z \in Z^{in}, z' \in Z_z^T, m \in M_{(z,z')}^{TT}, t \in T \quad (5-8)$$

The  $\gamma$  parameters provide lower and upper bounds to the capacity expansion for each technology while parameters  $\mu_{(z,m,t)}$  (or  $\mu_{(z,z',m,t)}^{TT}$ ) represent the necessary installation duration after which a technology capacity expansion becomes available.

### 5.6.2 Linking Constraints for Design and Planning

For each zone and time period, design and planning decisions are connected by the following set of constraints that provide lower and upper bounds on the operational level ( $P_{(z,z',i,m,t)}$ ) of each conversion, local exploitation and transfer technology through the total installed capacity of the corresponding technology:

$$\alpha_{(z,z',j,m,t)}^{\min} FC_{(z,m,t)} \leq P_{(z,z',j,m,t)} \leq \alpha_{(z,z',j,m,t)}^{\max} FC_{(z,m,t)} \quad \forall z \in Z^{in}, s \in S_z, j \in J_s^+, m \in (M_z^{CE} \cap M_j), t \in T \quad (5-9)$$

$$\begin{aligned} \alpha_{(z,z',j,m,t)}^{\min} F^T_{(z,z',m,t)} &\leq P_{(z,z',j,m,t)} \leq \alpha_{(z,z',j,m,t)}^{\max} F^T_{(z,z',m,t)} \\ &\forall z \in Z, z' \in Z_z^T, s \in S_z, j \in J_s^{TT}, m \in (M_{(z,z')}^{TT} \cap M_j), t \in T \end{aligned} \quad (5-10)$$

Parameters  $\alpha_{(z,z',j,m,t)}^{\min}$  and  $\alpha_{(z,z',j,m,t)}^{\max}$  are expressed as percentages and represent minimum and maximum availability factors of the total installed capacity of each technology, respectively.

For each zone and time period, bounds on the storage level ( $B_{(z,s,t)}$ ) for each storable state are also imposed through the total installed capacity of the corresponding storage technology, as given by:

$$\beta_{(z,s,t)}^{\min} \sum_{m \in M_{(s,z)}^{ST}} FC_{(z,m,t)}^{ST} \leq B_{(z,s,t)} \leq \beta_{(z,s,t)}^{\max} \sum_{m \in M_{(s,z)}^{ST}} FC_{(z,m,t)}^{ST} \quad \forall z \in Z^{in}, s \in S_z^B, t \in T \quad (5-11)$$

Parameters  $\beta_{(z,s,t)}^{\min}$  and  $\beta_{(z,s,t)}^{\max}$  are expressed as percentages and represent safety inventory levels and maximum availability of storage capacity, respectively.

### 5.6.3 Planning Constraints

#### 5.6.3.1 Raw Materials States Availability

In this study, the ‘raw materials’ states  $s \in S_z^{RM}$ , which correspond to principal input states (any type of states), categorised into renewables and non-renewables ( $s \in S^{NR}$ ) are defined. For each renewable state per zone and time period, the amount of the renewable state consumed by tasks  $j \in J_s^{RM}$  through local exploitation technologies  $m \in M_z^E$  plus the amount of the renewable state transferred to other zones cannot exceed the maximum available amount of this state  $\omega_{(z,s,t)}$ , according to:

$$\sum_{j \in J_s^{RM}} \sum_{m \in (M_z^E \cap M_j)} P_{(z,z,i,m,t)} + \sum_{j \in J_s^{TR}} \sum_{m \in (M_{(z,z')}^{TR} \cap M_j)} \sum_{z' \in Z_z'} P_{(z,z',j,m,t)} \leq \omega_{(z,s,t)} \quad \forall z \in Z, s \in S_z^{RM} : s \notin S^{NR}, t \in T \quad (5-12)$$

For each zone, the total availability for each non-renewable raw material state ( $\omega_{(z,s)}^{NR}$ ) throughout the whole time horizon is constrained by:

$$\sum_{t \in T} \sum_{j \in J_s^{RM}} \sum_{m \in (M_z^E \cap M_j)} \sum_{t \in T} P_{(z,z,j,m,t)} \leq \omega_{(z,s)}^{NR} \quad \forall z \in Z^{in}, s \in (S_z^{RM} \cap S^{NR}) \quad (5-13)$$

#### 5.6.3.2 States Connection and Balance

Constraints (5-14) express the states connection and balance in each zone at the end of each time period. According to these constraints, the inventory level of storable states  $s \in S_z^B$  at the end of each time period per zone depend on: (i) the inventory at the end of the previous time period  $B_{(z,s,t-1)}$  considering some losses  $\eta_{(z,s,t)}$ , (ii) the given demand, if any, (iii) the lost sales, (iv) the disposed amount, (v) the amount produced from local exploitation tasks (if the state is a raw material state), (vi) the inlet or outlet transferred amount, and (vii) the amount produced



by task  $i \in I_s^+$  or consumed by task. For any state that cannot be stored ( $s \notin S_z^B$ ), the state balance considers only: (i) the given demand, if any, (ii) the lost sales, (iii) the disposed amount, (iv) the amount produced from local exploitation tasks (if the state is a raw material state), (v) the inlet or outlet transferred amount, and (vi) the amount produced by task  $i \in I_s^+$  or consumed by  $i \in I_s^-$ .

$$\begin{aligned}
B_{(z,s,t)} = & (1 - \eta_{(z,s,t)}^{loss}) B_{(z,s,t-1)} - \zeta_{(z,s,t)} + L_{(z,s,t)} - DB_{(z,s,t)} + \overbrace{\sum_{j \in J_s^{RM}} \sum_{m \in (M_z^E \cap M_j)} P_{(z,z,j,m,t)}}^{\text{production: local exploitation tasks}} \\
& + \overbrace{\sum_{z' \in Z_s^I} \sum_{j \in J_s^{IT}} \sum_{m \in (M_{(z,z')}^{IT} \cap M_j)} \kappa_{(s,j,m)}^+ P_{(z',z,j,m,t)}}^{\text{inlet flow from transfer tasks}} - \overbrace{\sum_{z' \in Z_s^I} \sum_{j \in J_s^{IT}} \sum_{m \in (M_{(z,z')}^{IT} \cap M_j)} \kappa_{(s,j,m)}^- P_{(z,z',j,m,t)}}^{\text{outlet flow from transfer tasks}} \\
& + \overbrace{\sum_{j \in J_s^+} \sum_{m \in (M_z^{CE} \cap M_j)} \kappa_{(s,j,m)}^+ P_{(z,z,j,m,t)}}^{\text{production from conversion tasks}} - \overbrace{\sum_{j \in J_s^-} \sum_{m \in (M_z^{CE} \cap M_j)} \kappa_{(s,j,m)}^- P_{(z,z,j,m,t)}}^{\text{consumption from conversion tasks}} \quad \forall z \in Z, s \in S_z, t \in T
\end{aligned} \tag{5-14}$$

$$\begin{aligned}
B_{(z,s,t=0)} &= \beta_{(z,s)}^0 \quad \forall z \in Z, s \in S_z^B \\
B_{(z,s,t)} &= 0 \quad \forall z \in Z, s \notin S_z^B, t \in T \\
DB_{(z,s,t)} &= 0 \quad \forall z \in Z, s \notin S_z^D, t \in T
\end{aligned}$$

Parameters  $\beta_{(z,s)}^0$  correspond to the initial inventory of each storable states  $s \in S_z^B$ . Losses coefficients are set to zero for all storable states in the first time period. Parameters  $\kappa_{(s,j,m)}^{+/-}$  represent coefficients related to conversion and transfer tasks. Inventory levels of non-storable states and disposal levels for non-disposable states are set to zero.

#### 5.6.4 Economics Equations

In this part, the major cost equations for the design and planning problem of a general energy supply chain are presented.

Fixed assets costs for conversion, local exploitation and storage technologies correspond to the investment required for establishing and expanding the technologies, as given by:

$$FA_t = \sum_{z \in Z^{in}} \sum_{m \in M_z^{CE}} (\varepsilon_{(z,m,t)}^{CES0} WC_{(z,m,t)} + \varepsilon_{(z,m,t)}^{CES} EC_{(z,m,t)}) + \sum_{z \in Z^{in}} \sum_{s \in S_z^B} \sum_{m \in M_{(s,z)}^{ST}} (\varepsilon_{(z,m,t)}^{CES0} WS_{(z,s,m,t)} + \varepsilon_{(z,m,t)}^{CES} EC_{(z,s,m,t)}^{ST}) \quad \forall t \in T \tag{5-15}$$

Fixed assets costs for transfer technologies correspond to the total investment for creating a transfer network between two zones and is associated with the fixed investment required to install a transfer technology and the investment required (per unit) for increasing the capacity of transfer technology:

$$FA_t^{TS} = \sum_{z \in Z^m} \sum_{z' \in Z_z^T} \sum_{m \in M_{(z',z)}^{TT}} (\varepsilon_{(z,z',m,t)}^{TT0} Y_{(z,z',m,t)}^{TT} + \varepsilon_{(z,z',m,t)}^{TT} EC_{(z,z',m,t)}^{TT}) \quad \forall t \in T \quad (5-16)$$

Fixed operating costs are considered to be proportional to the total capacity of all conversion and local exploitation technologies installed, according to:

$$FOC_t = \sum_{z \in Z^m} \sum_{m \in M_z^{CE}} \phi_{(z,m,t)} FC_{(z,m,t)} \quad \forall t \in T \quad (5-17)$$

Variable costs consist of costs related to raw materials, production, inventory, transfer, disposal and lost sales costs:

$$VOC_t = RC_t + PC_t + IC_t + TC_t + DC_t + LS_t \quad \forall t \in T \quad (5-18)$$

The raw materials cost consists of the cost required for the consumption of raw material states by tasks through local exploitation technologies:

$$RC_t = \sum_{z \in Z^m} \sum_{s \in S_z^{RM}} \sum_{j \in J_s^{RM}} \sum_{m \in (M_z^E \cap M_s \cap M_j)} \psi_{(z,s,j,m,t)}^{RM} P_{(z,z,j,m,t)} \quad \forall t \in T \quad (5-19)$$

The production cost is associated to the cost needed for producing states through local exploitation or conversion technologies:

$$PC_t = \sum_{z \in Z^m} \sum_{s \in S_z} \sum_{j \in J_s^+} \sum_{m \in (M_z^{CE} \cap M_j)} \pi_{(z,s,j,m,t)} P_{(z,z,j,m,t)} \quad \forall t \in T \quad (5-20)$$

The inventory cost for storable states is given by:

$$IC_t = \sum_{z \in Z^m} \sum_{s \in S_z^B} \lambda_{(z,s,t)}^{ST} B_{(z,s,t)} \quad \forall t \in T \quad (5-21)$$

The transfer cost includes the transfer cost of any state (including states with demands or not as well as raw material states) that could be transferred between any pair of zones:

$$TC_t = \sum_{z' \in Z} \sum_{z \in Z_z^T} \sum_{s \in (S_z \cap S_{z'})} \sum_{j \in J_s^{IT}} \sum_{m \in (M_{(z',z)}^{IT} \cap M_j)} \vartheta_{(z',z,s,j,m,t)}^{IT} P_{(z',z,j,m,t)} \quad \forall t \in T \quad (5-22)$$

The disposal cost represents the corresponding cost for disposing the disposable states  $s \in S_z^D$  to the environment (e.g., carbon tax or other emissions related costs) or other destinations:

$$DC_t = \sum_{z \in Z^{in}} \sum_{s \in S_z^D} \lambda_{(z,s,t)}^D DB_{(z,s,t)} \quad \forall t \in T \quad (5-23)$$

Lost sales represents the associated costs for the unsatisfied demand of demand-states  $s \in S_z^{FP}$ :

$$LS_t = \sum_{z \in Z^{in}} \sum_{s \in S_z^{FP}} \lambda_{(z,s,t)}^L L_{(z,s,t)} \quad \forall t \in T \quad (5-24)$$

### 5.6.5 Objective Function

The optimisation goal is the minimization of the total cost that involves fixed assets costs for technologies, and fixed and variable operating costs, as defined in the previous subsections:

$$\min \sum_{t \in T} (FA_t + FA_t^{TS} + FOC_t + VOC_t) \quad (5-25)$$

### 5.6.6 Remarks

Note that the proposed mathematical model can readily address other objective functions, such as the net present value, or multi-objective optimisation problems through the use of relevant methods (e.g.,  $\epsilon$ -constraint method). It should be also mentioned that the definition of zones and the duration of each time period is problem specific and depends on the associated decision maker. For instance, in the national power grid case, the power system is divided in zones according to the division of the transmission lines network and major producers and consumers. This is usually a geographical division, but it could be done following other criteria as well. Regarding the length of the time periods, in the design problem it is common to consider yearly periods, since these problems

correspond to major strategic decisions. The total time horizon for design problems usually varies for 15 to 30 years. For planning problems, the length of the time periods can be months, weeks or even days. The same applies to the total time horizon for planning problems.

## **5.7 Case Studies**

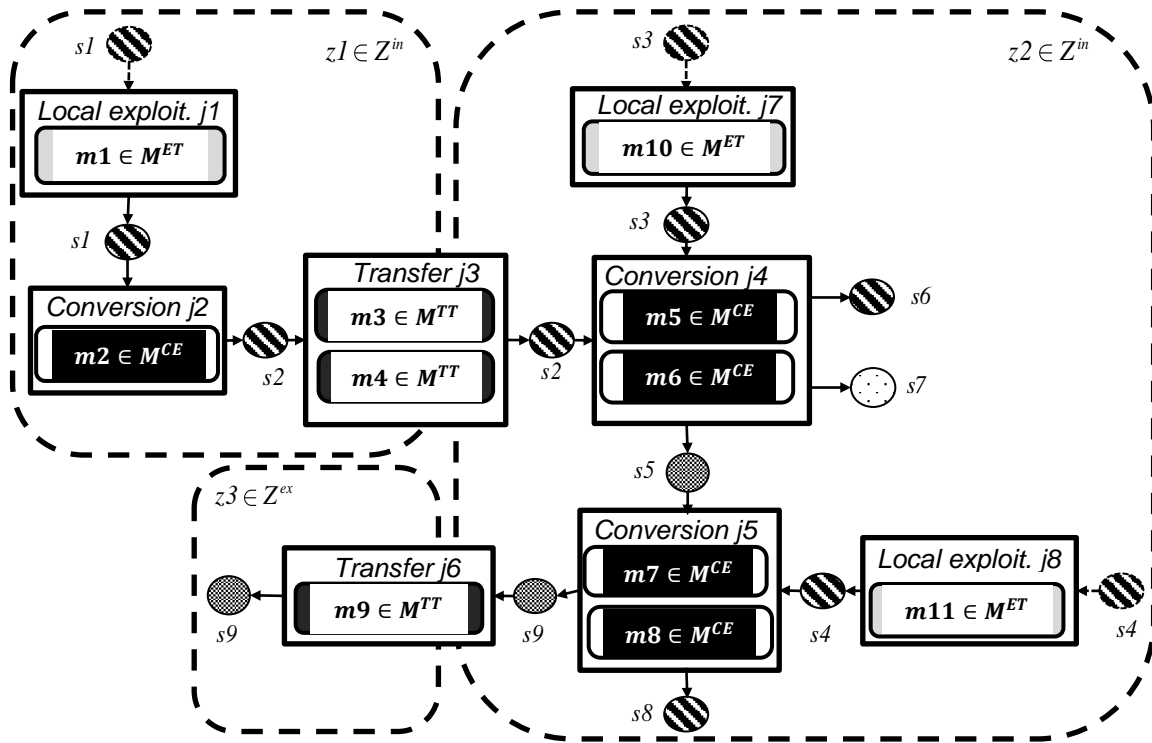
In this section, three cases for the design and planning problem of a mixed material-based and energy supply chain network are presented in order to highlight the special features of the proposed optimisation framework. More specifically, the first case introduces the baseline energy supply chain design problem. The effect on the design of the energy supply chain network by increasing the emissions costs and by imposing bounds on the generated emissions levels are studied in the second and third case, respectively. In the last part of this section, to highlight the some types of analyses that the proposed approach could be used, a sensitivity analysis study with respect to alternative emissions caps and a multi-objective optimisation example considering the conflicting objectives of total cost and emissions are presented. The proposed optimisation framework have been written in GAMS 24.8 (Brooke, et al., 1998) and solved with the MIP solver CPLEX 12.7 (ILOG, 2017) in an Intel(R) core(TM) i7-6700CPU@ 3.4 GHz with 8 GB RAM under standard configurations and a zero optimality gap. All solutions have been found in negligible computational times.

### **5.7.1 Case A: Design and Planning of an Energy Supply Chain Network**

#### **5.7.1.1 Description of Case A**

The system under consideration consists of nine states ( $s1 - s9$ ), among of which three states ( $s1, s3, s4$ ) are raw material states, two states ( $s5, s9$ ) are energy form states, three states ( $s2, s6, s8$ ) are energy material resources states and one state ( $s7$ ) is an undesired substance state. The energy material resources states can be stored in their respective storage tanks or can be disposed. The energy form states cannot be stored but they could be disposed to the environment. There are a total of eight tasks ( $j1 - j8$ ) in the network representation. The network consists

of three conversion tasks ( $j_2, j_4, j_5$ ), two transfer tasks ( $j_3, j_6$ ) and three local exploitation tasks ( $j_1, j_7, j_8$ ). For each task, there are associated technologies ( $m_1 - m_{11}$ ) are shown in Figure 3-4. There are also storage technologies for each storable state ( $js_1 - js_8$ ).



**Figure 5-4 E-STN representation for the energy supply chain network considered**

According to Figure 5-4, the raw material state  $s_1$  is converted into energy material resource state  $s_2$  by conversion task  $j_2$  that can be performed by conversion technology  $m_2$ . The energy material resource state  $s_2$  is transferred through transfer task  $j_3$  which includes two transfer technology  $m_3$  and  $m_4$ . Then, energy material resource state  $s_2$  reacts with raw material state  $s_3$  in conversion task  $j_4$  that can be performed by conversion technologies  $m_5$  and  $m_6$  to produce energy material state  $s_6$ , energy form state  $s_5$  and undesired substances states  $s_7$ . This type of conversion task can be a typical steam methane reforming plant, in which methane reacts with water to produce hydrogen, heat and carbon dioxide. Meanwhile, in conversion task  $j_5$  which

could be performed by conversion technologies  $m7$  and  $m8$ , utilises the energy form state  $s5$  and reacts with raw material state  $s4$  to produce energy material resource state  $s8$  and energy form state  $s9$ . This type of conversion task can be a combined heat and power (CHP) that uses natural gas as fuels for boilers operations and additional heat from steam methane reforming plant to produce electricity and pressurised steams.

The energy form state  $s9$  in zone 2 can be sold and transferred to the external energy network (e.g., zone 3) through transfer task  $j6$ . The available storage technology per state and zone is displayed in Table 5-1.

**Table 5-1 Available storage technologies per state and zone**

Storable States	$z1$	$z2$
$s1$	$js1$	-
$s2$	$js2$	$js2$
$s3$	-	$js3$
$s4$	-	$js4$
$s6$	-	$js6$
$s8$	-	$js8$

The minimum ( $\alpha_{(z,z',s,j,m,t)}^{min}$ ) and maximum ( $\alpha_{(z,z',s,j,m,t)}^{max}$ ) availability percentage of output states from task  $j \in J_s^+$  is equal to 0 and 1, respectively. For the states that can be stored, the minimum inventory level ( $\beta_{(z,s,t)}^{min}$ ) is equal to 0.5 and maximum inventory level ( $\beta_{(z,s,t)}^{max}$ ) is equal to 1. The coefficients for the input states of task  $j \in J_s^-$  and output states of task  $j \in J_s^+$  that can be performed by technology  $j$  are given in Table 5-2 and Table 5-3, respectively.

**Table 5-2 Coefficients  $\kappa_{(s,j,m)}^-$  for input states for tasks  $j \in J_s^-$  that can be performed by technologies  $m$**

State	Task	$m2$	$m3$	$m4$	$m5$	$m6$	$m7$	$m8$	$m9$
$s1$	$j2$	1	-	-	-	-	-	-	-
$s2$	$j3$	-	1	1	-	-	-	-	-
$s2$	$j4$	-	-	-	0.5	0.5	-	-	-
$s3$	$j4$	-	-	-	0.5	0.5	-	-	-
$s4$	$j5$	-	-	-	-	-	1	1	-
$s5$	$j5$	-	-	-	-	-	1.5	1.5	-
$s9$	$j6$	-	-	-	-	-	-	-	1

**Table 5-3 Coefficients  $\kappa_{(s,j,m)}^+$  for output states for tasks  $j \in J_s^+$  that can be performed by technologies  $m$**

State	Task	$m2$	$m3$	$m4$	$m5$	$m6$	$m7$	$m8$	$m9$
$s2$	$j2$	1	-	-	-	-	-	-	-
$s2$	$j3$	-	1	1	-	-	-	-	-
$s5$	$j4$	-	-	-	1	1	-	-	-
$s6$	$j4$	-	-	-	1	1	-	-	-
$s7$	$j4$	-	-	-	5	10	-	-	-
$s8$	$j5$	-	-	-	-	-	1	1	-
$s9$	$j5$	-	-	-	-	-	1	1	-
$s9$	$j6$	-	-	-	-	-	-	-	1

Table 5-4 provides the investment cost, fixed operating cost and production cost with minimum and maximum capacity installed per technology. As the number of time period increases, the investment cost to establish the technology  $\varepsilon_{(z,m,t)}^{CES0}$  increases by a factor of 1.01 to 1.5 from the cost of the previous time period. The investment cost to establish storage technology is 1,000 (m.u./unit) and increases by a factor of 1.005 from the cost of the previous time period. The investment cost to establish local exploitation technology increases over time period by this

expression:  $1,000(1.02^t)$ . The investment cost  $\varepsilon_{(z,m,t)}^{CES}$  for increasing the capacity of a technology varies within a certain range. In addition, the initial inventory cost  $\lambda_{(z,s,t)}^{ST}$  for all states  $s \in S^B$  is 0.1 m.u./unit and increases by a factor of 1.05 from the cost of the previous time period. The initial emissions cost  $\lambda_{(z,s,t)}^D$  for undesired substances state  $s7$  is 18 m.u./unit, and increases over time by this expression:  $1+0.05 \lambda_{(z,s,t-1)}^D$ . The initial disposable costs  $\lambda_{(z,s,t)}^D$  for other states are very high at about 500 m.u./unit and increases by a factor of 1.1 from the costs of the previous time period. The disposable costs for other states are fixed to high values to avoid energy material resources or energy form states to be disposed to the environment. The necessary installation time ( $\mu_{(z,m,t)}^{CE}$ ) for conversion and local exploitation technology is equal to one period while for storage technologies ( $\mu_{(z,m,t)}^{ST}$ ) is considered zero.

**Table 5-4 Investment cost, fixed operating cost and production cost with minimum and maximum capacity installed per technology**

Technology	$\gamma^{min}$	$\gamma^{max}$	$\varepsilon_{(z,m,t)}^0$ (m.u./unit)	$\varepsilon_{(z,m,t)}$ (m.u./unit)	$\phi_{(z,m,t)}$ (m.u./unit)	$\pi_{(z,s,j,m,t)}$ (m.u./unit)
<i>j1</i>	50	50	(1,326-1,820)	(1,122-1,540)	-	-
<i>j2</i>	5	50	20,000	(1,300-2,000)	15	12
<i>j5</i>	10	40	28,000	(3,800-4,200)	20	20
<i>j6</i>	10	40	25,000	(2,500-3,200)	40	25
<i>j7</i>	5	30	20,000	(1,900-2,200)	30	30
<i>j8</i>	5	30	26,000	(1,800-2,200)	25	40
<i>j10</i>	50	50	(1,326-1,820)	(1,122-1,540)	-	-
<i>j11</i>	50	50	(1,326-1,820)	(1,122-1,540)	-	-
<i>j3</i>	0	30	2,000	(1,000-1,300)	0	0
<i>j4</i>	0	30	2,000	(1,000-1,300)	0	0
<i>j9</i>	0	50	2,000	(800-1,000)	0	0



A total planning horizon of 20 time periods is considered. It is assumed that the energy supply chain network did not exist before the beginning of the planning horizon of interest, therefore there is no initial state (i.e.,  $\beta_{(z,s)}^0, \varphi_{(z,m)}, \varphi_{(z,s,m)}^{ST}$  and  $\varphi_{(z,z',m)}^{TT}$ ) that is taken into account for this case study.

Figure 5-5 displays the normalised demand profiles for states ( $s \in S^{FP}$ ) per zone by having as a reference the highest demand observed for each state throughout the planning horizon.

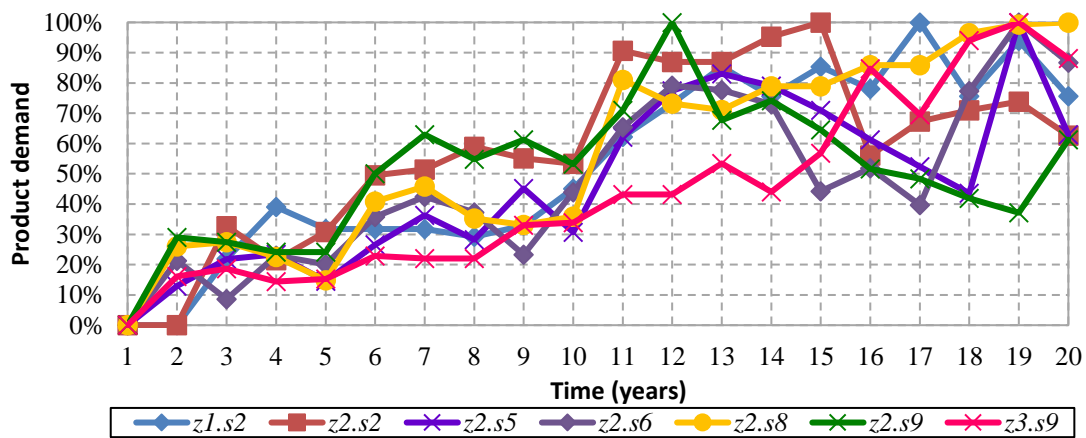
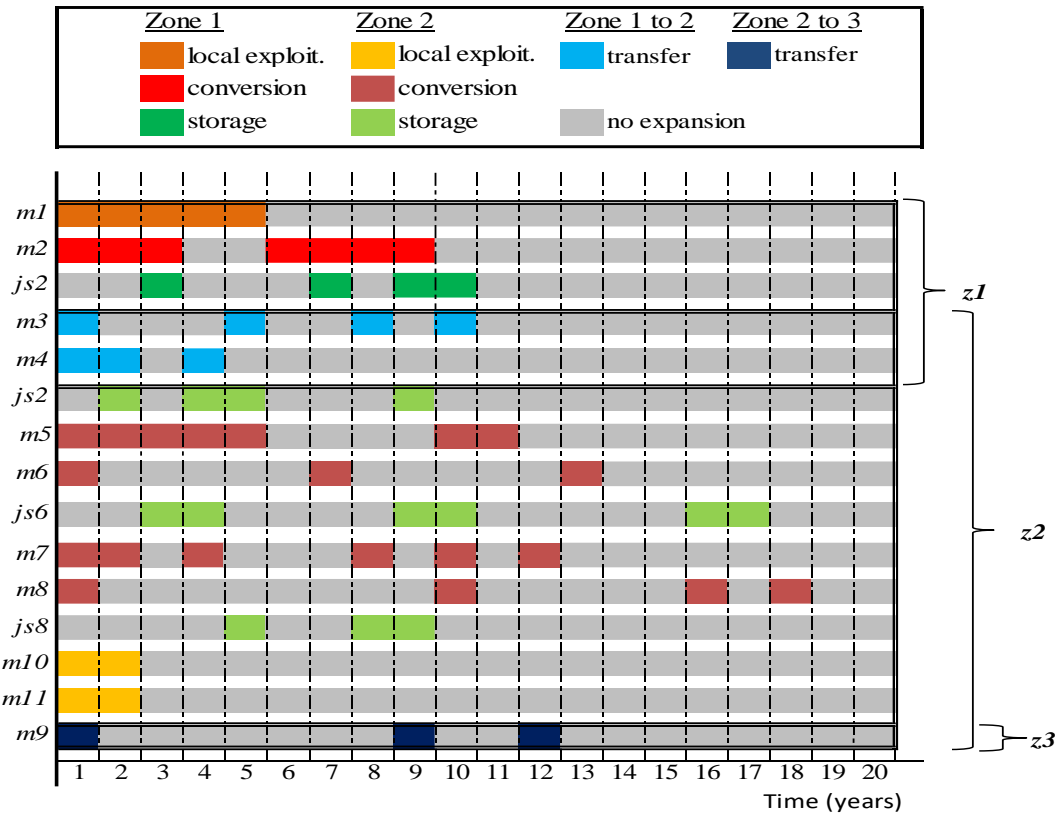


Figure 5-5 Demand profiles for states  $s \in S^{FP}$  for all case studies

### 5.7.1.2 Results of Case A

Figure 5-6 displays the optimal capacity expansion planning for conversion ( $m3, m4, m9$ ), local exploitation ( $m1, m10, m11$ ), transfer ( $m3, m4, m9$ ) and storage technologies ( $js2, js6, js8$ ) for the planning horizon of interest (i.e., binary variables  $YC, YT, YS$ ). All local exploitation, conversion and transfer technologies are established in the first time period because there was no initial installed capacity for any of the technologies, there are demands for states from the second time period and on, and the establishment costs for these technologies are lower in the first time periods. Since in this example, a construction time for these technologies equal to one time period is considered, most storage technologies are established in next time periods when production of storable states could occur. For instance, storage technology  $js2$  in  $z1$  is first established

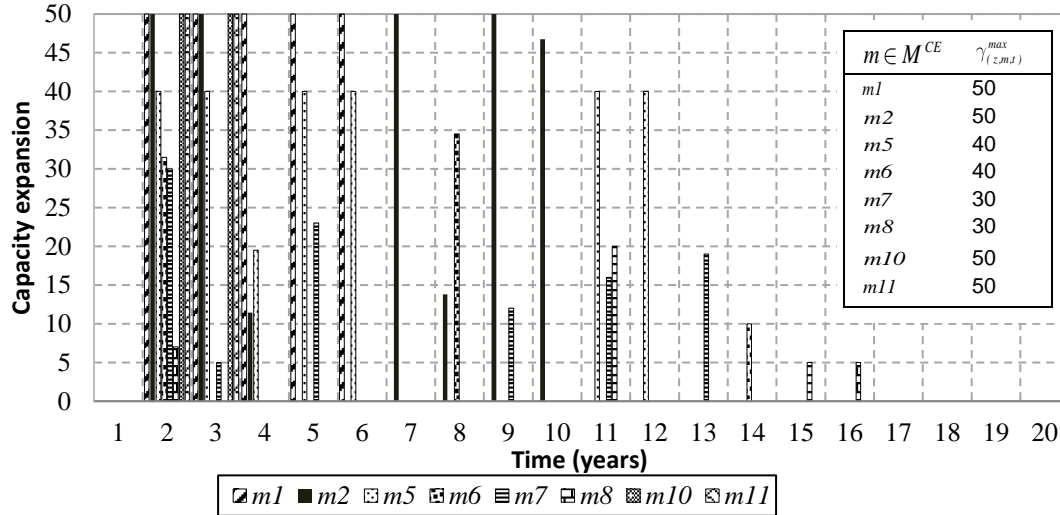
in the third time period while storage technologies  $js2$ ,  $js6$  and  $js8$  in  $z2$  are established in the second, third and fifth time period (see Figure 5-6).



**Figure 5-6 Case A: Capacity expansion planning per technology, zone and time period**

The capacity expansion for each technology usually takes place in early time period (from time period 1 to time period 16) because the investment costs to establish the technology ( $\varepsilon_{(z,m,t)}^{CES0}$ ) and investment cost to increase the capacity of technology ( $\varepsilon_{(z,m,t)}^{CES}$ ) are generally cheaper in earlier time periods than in the later time periods (time period 17 onwards). For example, the latest time period to establish transfer technologies are not more than 16 time period (e.g.,  $m9$  is established by the latest time period 12) because the investment cost to increase the capacity of its transfer technology ( $\varepsilon_{(z,m,t)}^{TT}$ ) starts to increase in time period 17. Similarly, the capacity expansion of conversion technologies also occurs in early time periods. Observe that there is a capacity expansion for conversion

technology  $m8$  in later time periods (e.g., time period 16 and 18) in order to meet higher demand for state  $s8$  in the following time periods 17 to 20 (see Figure 5-5).

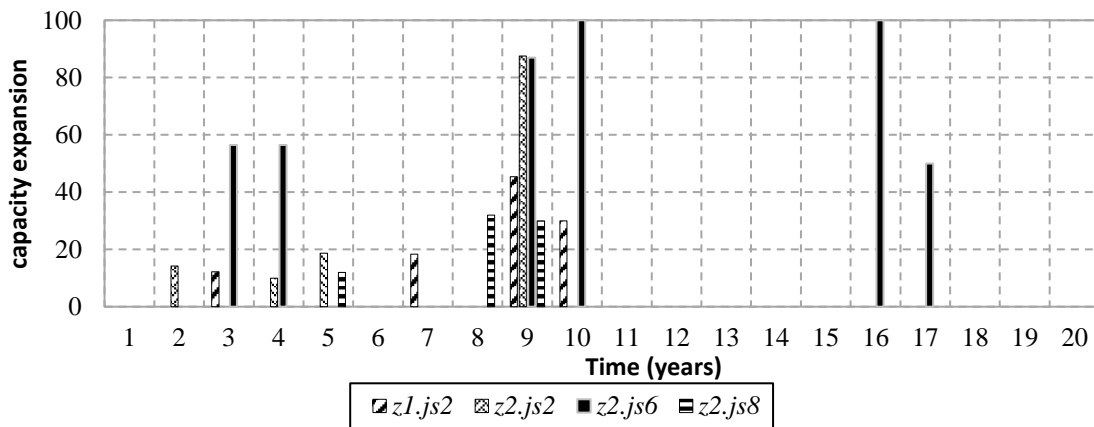


**Figure 5-7 Case A: Capacity expansion for local exploitation and conversion technologies per time period**

Figure 5-7 shows the capacity expansion levels for local exploitation and conversion technologies per time period of planning horizon. Recall that the installation time to construct each conversion technology is one time period. For example, local exploitation technologies  $m1, m10, m11$  and conversion technologies  $m2, m5, m6, m7, m8$  are established in time period 1 (refer to Figure 5-6). These capacity expansions are available in the next time period (e.g., time period 2). The higher capacity expansion for technologies is observed in time period 2 for  $m1, m2, m5, m7, m10$  and  $m11$  due to cheaper investment costs to establish the local exploitation and conversion technology ( $\varepsilon_{(z,m,t)}^{CES0}$ ) in early time period in comparison to the later time period. The investment cost to increase the capacity of established technologies ( $\varepsilon_{(z,m,t)}^{CES}$ ) also varies over time.

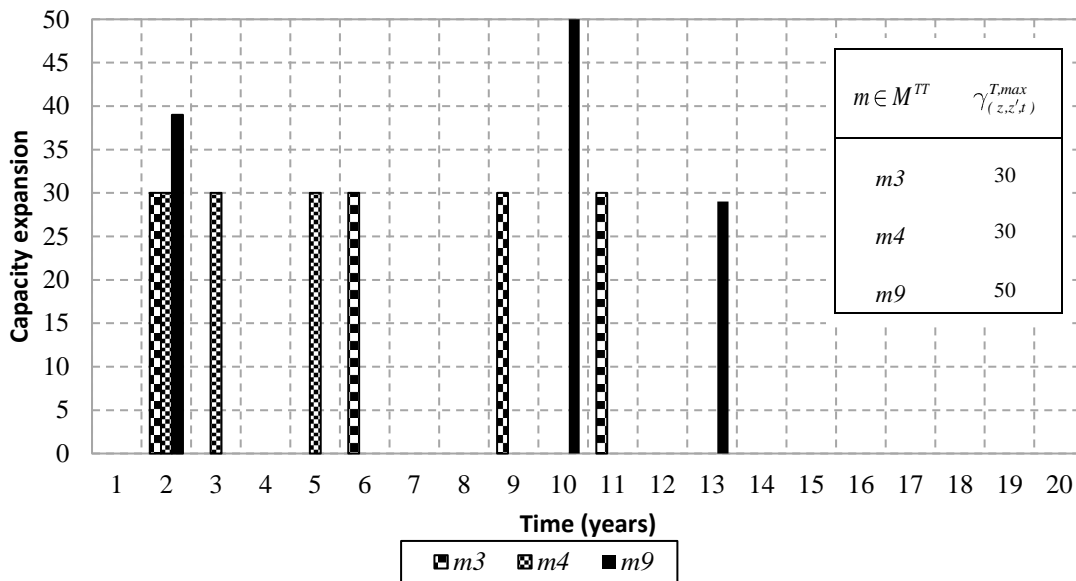
The capacity expansion of conversion technology  $m5$  is more preferable than that of conversion technology  $m6$  for conversion task  $j4$ , which is in time period 3 to 6, 11 and 12. This is because the emissions cost for conversion technology

$m5$  is lower than that of conversion technology  $m6$ . The reason is that, the coefficients of undesired substances state  $s7$  for output task  $j4$  that can perform conversion technology  $m5$  have half the values of the coefficients of undesired substances state  $s7$  for conversion technology  $m6$  (refer to Table 5-3). In addition, the capacity expansion investment cost for conversion technology  $m5$  is lower in these time periods. There is capacity expansion of conversion technology  $m6$  in time periods 8 and 14, because there is moderate production of undesired substances state  $s7$  in these time periods and the capacity expansion investment cost of conversion technology  $m6$  is lower than that of conversion technology  $m5$ . In addition, there is a higher installed capacity for conversion technology  $m7$  than that of  $m8$  for performing conversion task  $j5$  because of the lower investment costs of conversion technology  $m7$  in comparison to those of  $m8$ .



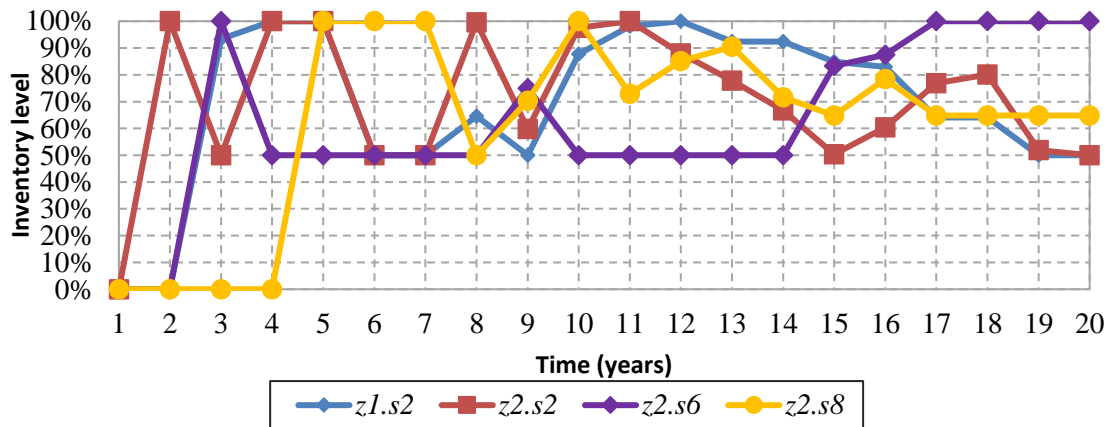
**Figure 5-8 Case A: Capacity expansion for storage technologies  $j \in J^B$  per zone and time period**

Figure 5-8 displays the capacity expansion profiles for storage technologies for the whole planning horizon. The expansion capacity for storage technology is assumed to be available at the same time period the storage technology is installed (see Figure 5-6 and Figure 5-8). There highest capacity expansion of storage technology  $js6$  is observed in time period 10 and 16, because of the high demand for state  $s6$  in the following time periods (refer to Figure 5-5).



**Figure 5-9 Case A: Capacity expansion for transfer technologies  $j \in J^T$  per time period**

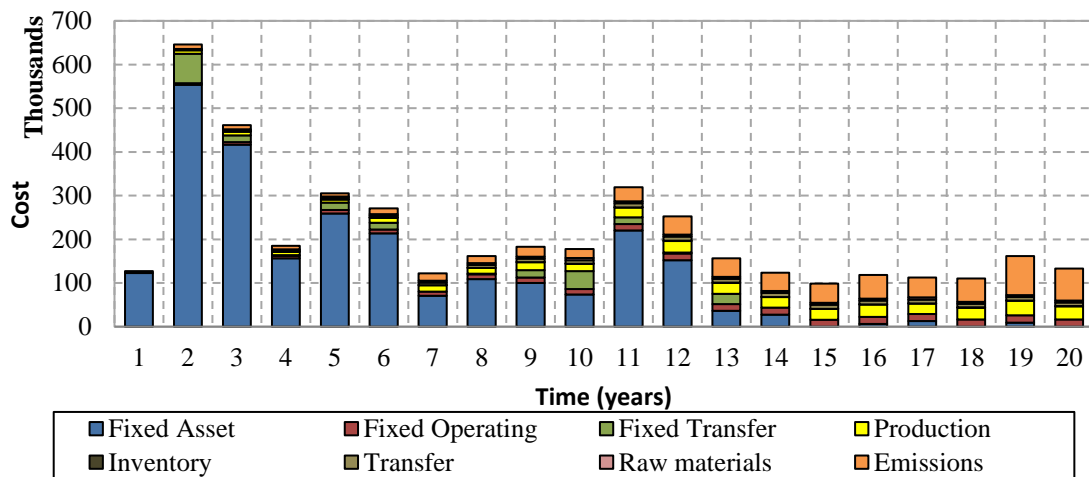
Figure 5-9 shows the capacity expansion for transfer technologies for the whole planning horizon. The installation time to construct each transfer technology is 1 time period. Similarly to local exploitation and conversion technologies, the expanded capacity for transfer technologies is available after one time period of the beginning of their installation (see Figure 5-6 and Figure 5-9). The highest capacity expansion for transfer technologies  $m3$  and  $m4$  to perform transfer task  $j3$  are observed in time period 2 because the investment cost to establish and to increase the capacity of transfer technology in early time periods is lower than that of the later time periods. The expansion capacity for transfer technology  $m9$  in time period 2 is 39 units. The quantity of state  $s9$  that is transferred through transfer technology  $m9$  from time period 2 until time period 9 must be less than or equal to 39. In time period 10, the expansion of transfer technology  $m9$  is needed to increase the transferred quantity of state  $s9$  to zone 3 from time period 10 to 12. In this case, the capacity of transfer technology  $m9$  increases to 89 units in time period 10. Then, there is another capacity expansion in time period 13 to further increase the transferred quantity of state  $s9$  to zone 3 from time period 13 and onwards.



**Figure 5-10 Case A: Inventory profiles for states per zone and time period**

Figure 5-10 shows the normalised inventory profiles for storable states. The reference values are the total installed capacity of storage technology that can store its respective states per time period. It is expected to observe that lower inventory levels occur in time periods with high demands for states. For example, a low inventory level for  $s2$  in  $z2$  is observed in time period 15 because there is a very high demand for  $s2$  in  $z2$  in this time period (see Figure 5-5).

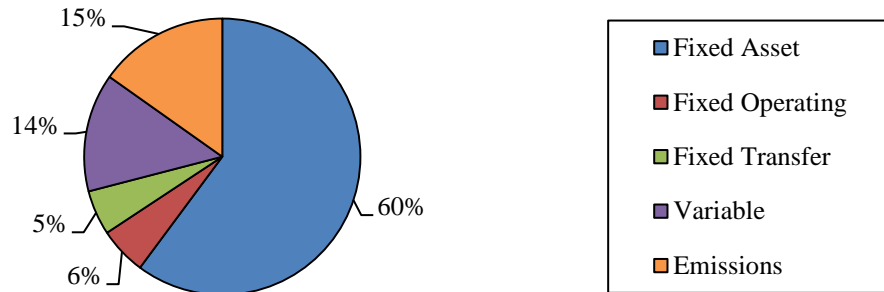
The inventory level of state  $s6$  from time period 17 to 20 reaches its maximum because of: (i) the expansion of storage technology  $js6$  in time period 16 and 17 (see Figure 5-8), (ii) the relatively low demand for state  $s6$  in time period 17, and (iii) the high demand for state  $s8$  in the last periods of the planning horizon. Although the demand for state  $s6$  increases from period 18 to 20, the inventory level is still at the maximum because the amount of state  $s6$  that is produced from task  $j4$  satisfies directly its demand. Finally, notice that there is no inventory level for state  $s8$  from time period 1 until 4 because the storage technology for  $s8$  (i.e.,  $js8$ ) has not been established yet in these periods (see Figure 5-6).



**Figure 5-11 Case A: Cost term breakdown throughout the planning horizon**

Figure 5-11 shows the breakdown of the total cost per associated cost and time period. The optimal solution reports a total cost of 4,226,906 relative money units (rmu). This total cost includes the following terms: (i) fixed asset cost (i.e., investment cost to establish and expand local exploitation, conversion and storage technologies), (ii) fixed operating cost (i.e., total capacity cost), (iii) fixed transfer cost (i.e., investment cost to establish and expand transfer technologies), (iv) production cost (i.e., cost for producing states through conversion technologies), (v) inventory cost (i.e., cost for storable states through storage technologies), (vi) transfer cost (i.e., cost for transferring states through transfer technologies), (vii) raw materials cost (i.e., cost for transferring raw materials states from local exploitation technologies), and (viii) emissions cost (i.e., carbon tax for the release of emission to the environment). Fixed assets and transfer costs are higher in earlier periods while fixed operating, production and emissions costs become higher as demands and the corresponding production of states increases over time. The highest fixed asset cost is observed in time period 2 because the investment cost to establish technologies ( $\varepsilon_{(z,m,t)}^{CES0}$ ) and investment cost to increase the capacity of technologies ( $\varepsilon_{(z,m,t)}^{CES}$ ) is lower than the investment costs in later time periods. Emissions cost increases over the time because of: (i) the expansion of conversion technologies  $m5$  and  $m6$  due to higher demands

for states  $s5$  and  $s6$ , and (ii) the increase of the emission cost coefficient over time.



**Figure 5-12 Case A: Total cost breakdown (percentage)**

Figure 5-12 shows the total cost breakdown for the problem under consideration. The fixed asset cost is the highest cost term at about 60% of the total cost. The second highest cost is the emissions cost at around 15% of the total cost followed by variable costs at 14%. Finally, the fixed operating and transfer cost count for the 6% and 5% of total cost, respectively.

## 5.7.2 Case B: Design and Planning of an Energy Supply Chain Network: the Effect of Increasing the Emissions Cost (Carbon Tax)

### 5.7.2.1 Description of Case B

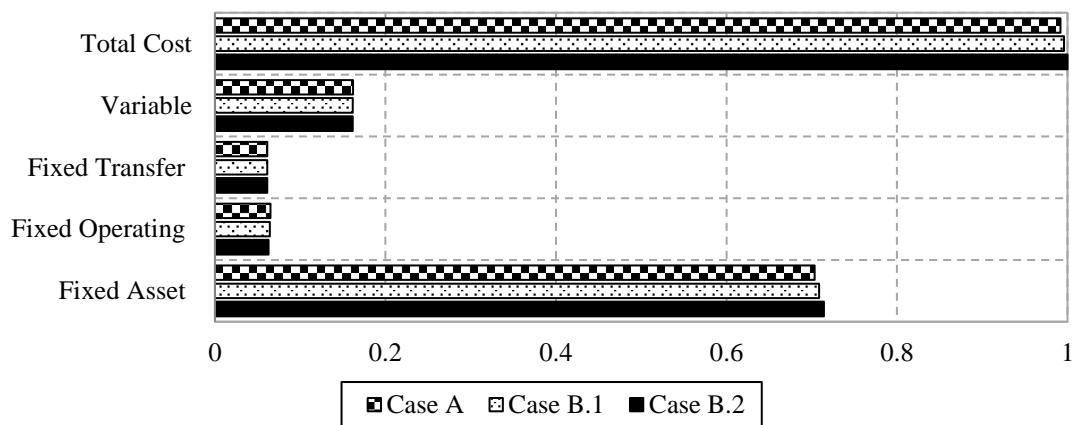
In this example, a slightly modified version of the previous case study is considered. All parameters and costs values are the same as before. The main difference is that the emissions costs  $\lambda_{(z,s,t)}^D$  (e.g., carbon tax prices) for undesired substance state  $s7$  is increasing over time. Case B is divided into two subcases: (i) Case B.1 (emission cost is two times the emission cost of Case A), and, (ii) Case B.2 (emission cost that is three times the emission cost of Case A).

### 5.7.2.2 Results of Case B

Figure 5-13 displays the normalised cost comparison of the solutions of all cases (Case A, Case B.1 and Case B2). Percentages are calculated by dividing each cost term with the highest total costs of the cases (i.e., that of Case B.2).



Emissions costs are not included in this figure because different coefficients are used for each problem instance. The results do not show big differences in variable, fixed transfer and operating costs among the different cases. The main differences observed, but still small, are in the fixed assets cost with Case B.2 having a slightly higher fixed assets cost than the other two cases. This is because of the higher levels of capacity expansion of more expensive but lower-emissions conversion technology  $m5$  in Case B.2 in comparison to that installed in Case B.1 and Case A. Consequently, the amount of states produced from task  $j4$  using conversion technology  $m5$  increases over the time, resulting in lower emissions generation than in other cases. The total installed capacity for conversion technology  $m5$  in Case B.1 and Case B.2 is more than that for conversion technology  $m6$  in Case A (see Figure 5-17).



**Figure 5-13 Cost terms comparison for cases A, B.1 and B2 (percentage)**

Figure 5-14 shows the aggregated total emissions for Case A, Case B.1 and Case B.2. As expected, Case A reports higher emissions levels than the other cases. Generally speaking, the higher the emissions costs, the lower the total emissions levels. Differences among the emissions levels of the different cases start being more visible from time periods that feature high demands for the states that can be produced by the task that has a by-product the undesired state (emissions). At the end of the time horizon considered, the differences in aggregated total emissions in comparison to Case A is 268 units for Case B.1 and 423 units for Case B.2. Overall, small reduction in the emissions levels have

been observed by imposing higher emissions costs and the overall design of the energy supply chain network has not been affected much. Increasing more dramatically the emissions costs is expected to have a higher effect on the optimal design of the network but from the practical point of view this could most probably result to unrealistically high emission costs.

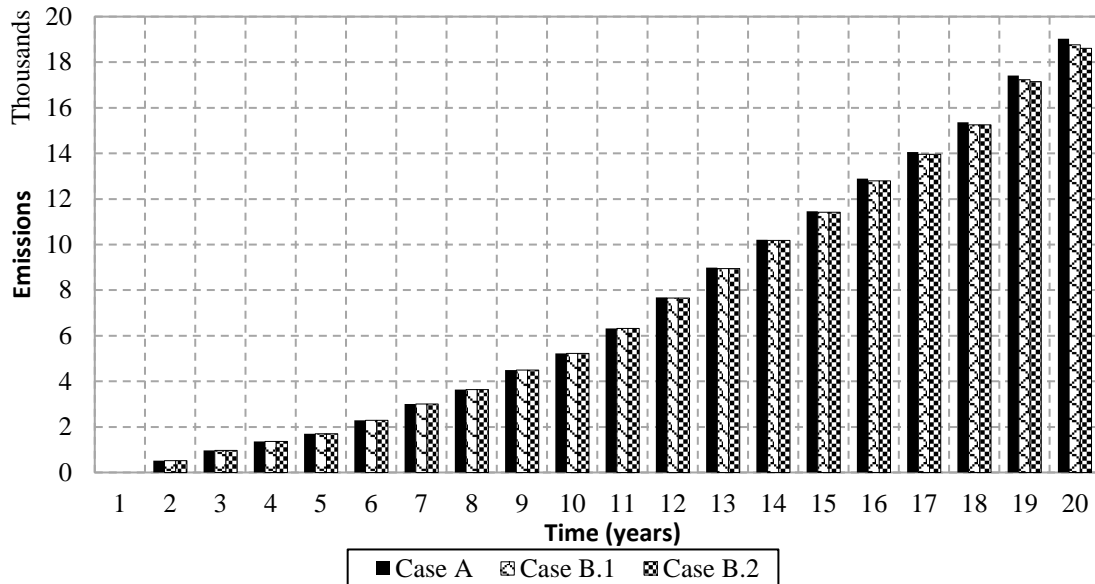


Figure 5-14 Aggregated total emissions per time period

### 5.7.3 Case C: Design and Planning of an Energy Supply Chain Network: the Effect of Emissions Levels Caps

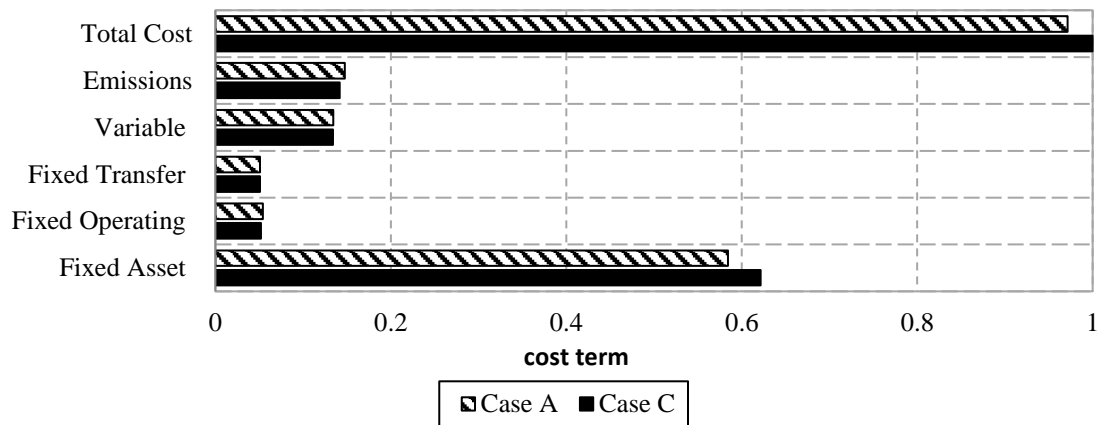
#### 5.7.3.1 Description of Case C

In this example, a slightly modified case study of Case A is considered by imposing an upper bound on the disposed amount of the states ( $DB_{(z,s,t)}$ ) for disposable state  $s \in S_z^D$  (i.e., emissions levels limits). The maximum amount of emissions per time period in the solution of Case A was 2,057.5 units. Here, in Case C, an upper bound of 1,700 units on the emissions per period is set.

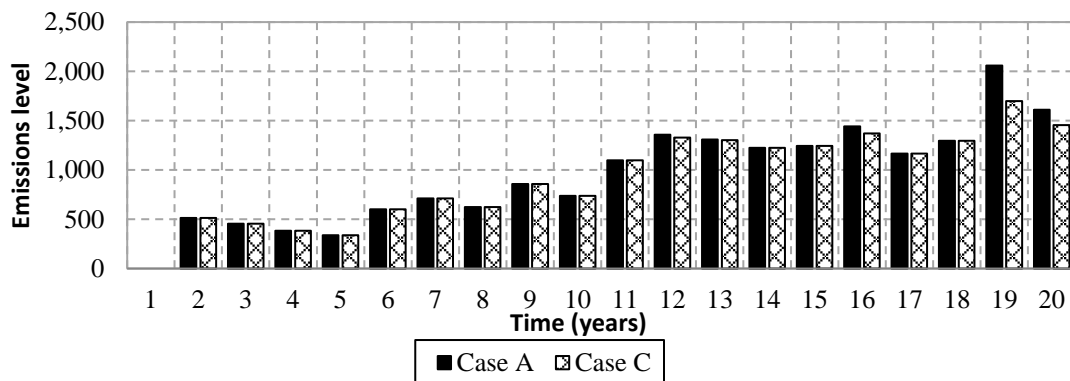
#### 5.7.3.2 Results of Case C

Figure 5-15 displays the percentage of cost comparisons for Case A and Case C. The emissions cost for Case C is 0.01 m.u lower than the emission cost for Case A. This is because the amount of disposed states is more limited through

the emissions levels cap. However, the fixed asset cost for Case C increases to 0.04 m.u in comparison to the fixed asset cost for Case A. In this case, the expansion to install conversion technology  $m5$  (more expensive but cleaner technology than conversion technology  $m6$ ) is more frequent than the conversion technology  $m6$  to perform task  $j4$ . This is a direct result of imposed upper bound on the emissions levels in Case C.



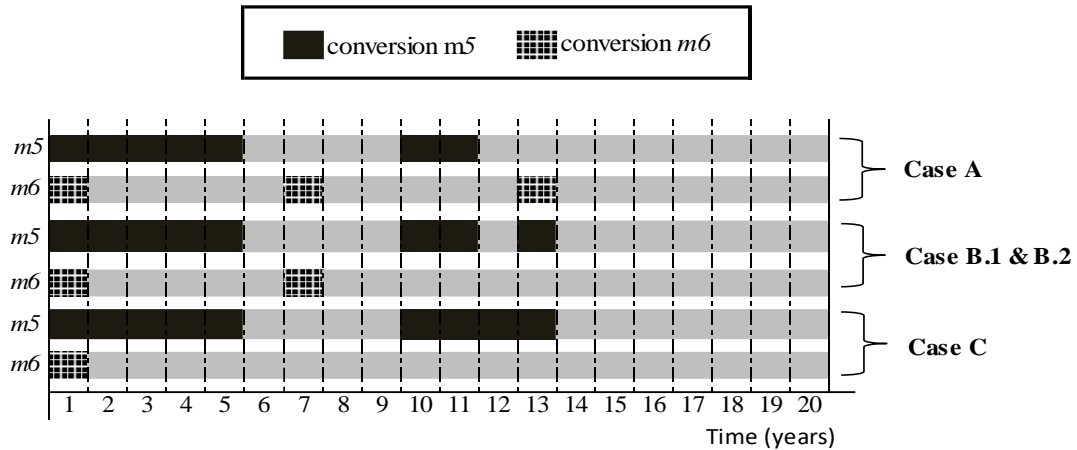
**Figure 5-15 Cost term comparison between Case A and C**



**Figure 5-16 Comparison of amount of disposable state  $s7$  (emissions) per time period between Case A and Case C**

Figure 5-16 shows the emissions level throughout the planning horizon. In this case, the disposable state is the only undesired substances state  $s7$  (emissions). There is reduction in emissions level in time period 12, 16, 19 and 20 for Case C in comparison to Case A. This is because, for task  $j4$  in Case C, conversion

technology  $m5$  has converted higher amounts of output states compared to conversion technology  $m6$  in these time periods compared to the solution of Case A. It is observed that a total emissions reduction of 3.3% in Case C with respect to Case A.



**Figure 5-17 Comparison of capacity expansion planning for conversion technologies  $m5$  and  $m6$  per time period for all cases**

Figure 5-17 shows the comparison of the capacity expansion planning for conversion technologies  $m5$  and  $m6$  per time period for all cases. As it has been discussed previously, there are more capacity expansions for conversion technology  $m5$  than that of conversion technology  $m6$  for Case C in comparison to Case A and Case B. In Case B.1 and Case B.2, the capacity expansion planning for these technologies is the same (i.e., variables  $Y$ ). However, a higher capacity expansion for conversion technology  $m5$  is reported in Case B.2 than in Case B.1. This case shows that emissions can be reduced imposing upper bounds on their generated levels (emissions caps by regulations).

Overall, through the case studies considered it is evident that for emissions reduction, specified emissions limits (e.g., carbon limits through regulations) are more effective than increasing the emissions cost. However, lower emissions limits would result in an increase in total costs due to the need for installing lower-carbon technologies that are typically more expensive than most conventional technologies at this time.

#### **5.7.4 Further Analyses: Sensitivity Analysis and Multi-Objective Optimisation**

In this part, some further illustrative analyses that could be performed by the proposed optimisation framework are presented. Figure 5-18 displays a sensitivity analysis for total emissions and costs with respect to alternative emissions caps, while Figure 5-19 presents total emissions reduction and cost increase (with respect to the emissions unconstrained case, i.e., Case A) per emissions caps scenario considered. These two figures give a complete picture of the trade-offs between total emissions and cost under varied emissions caps. It is observed that: (i) total cost increases significantly for emissions caps below 1,850 metric units, and (ii) the decrease rate for total emissions is higher for emissions caps above 1,900 metric units. It has been found that the minimum emissions cap possible is 1,678 metric units, since below this emissions cap value the resulting optimisation problem becomes infeasible (i.e., some demands for states cannot be satisfied completely). With respect to the emissions unconstrained case, the different emissions caps considered can achieve emissions reductions from 0.18% to 3.27% resulting to total cost increases from 0.01% to 2.95%, respectively. In practice, an emissions cap around 1,850 metric units could be considered as a good choice, since it would reduce emissions by 2.36% requiring a moderate cost increase by 0.48%.

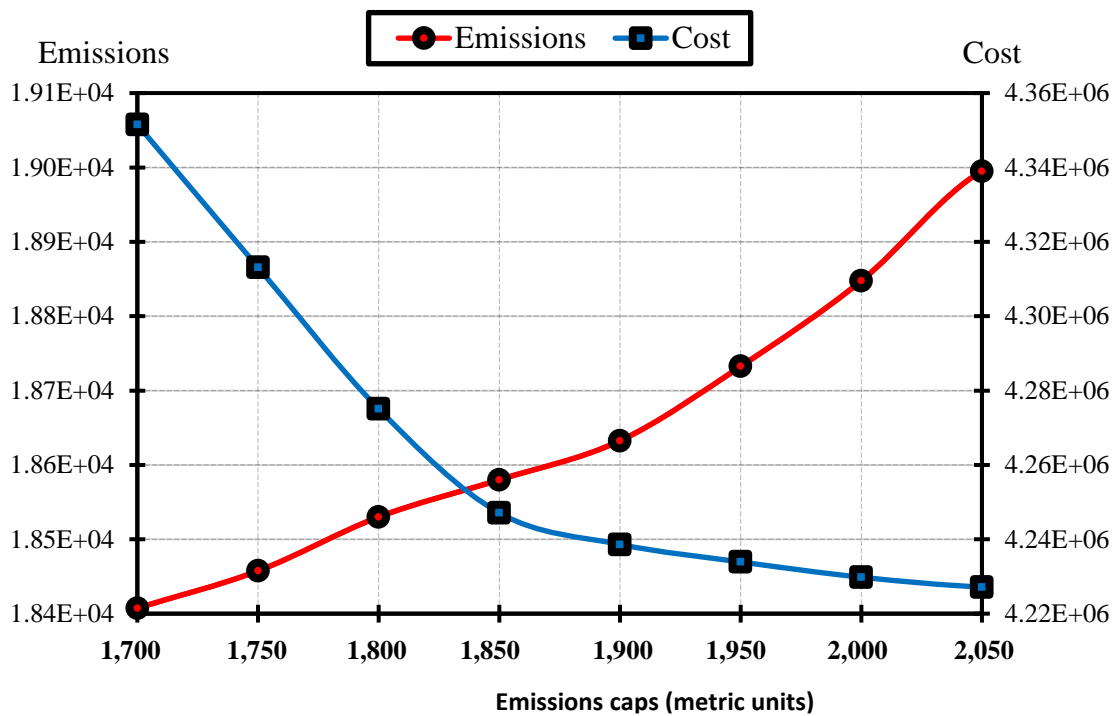


Figure 5-18 Sensitivity analysis for total emissions and cost under different emissions caps

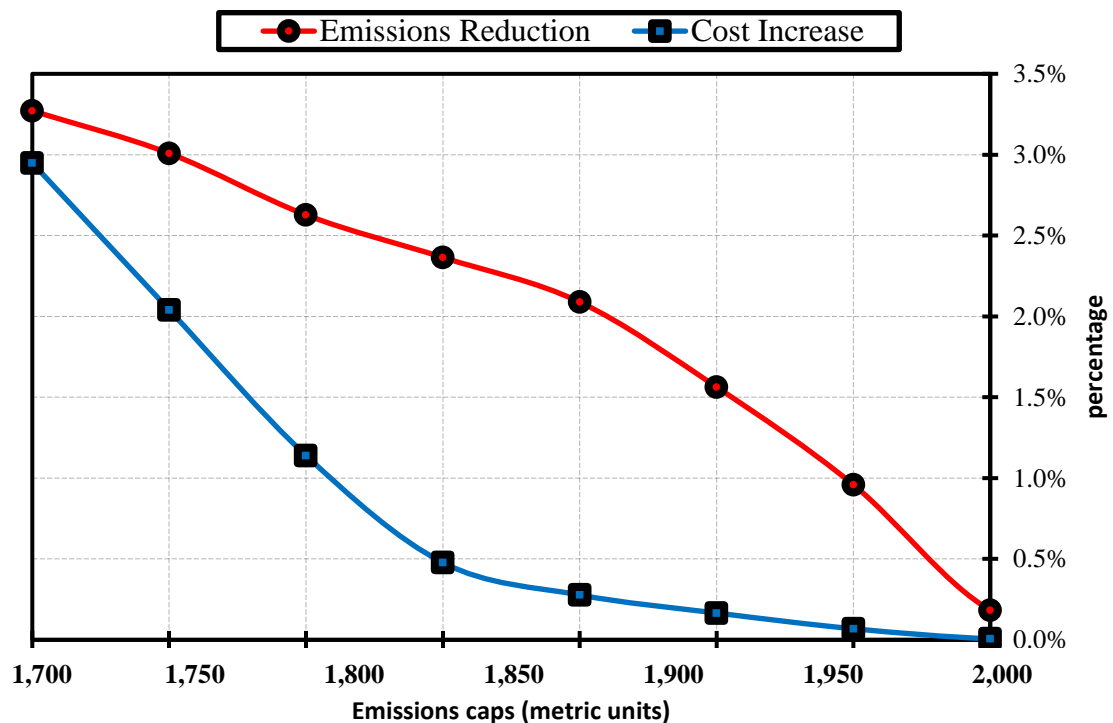
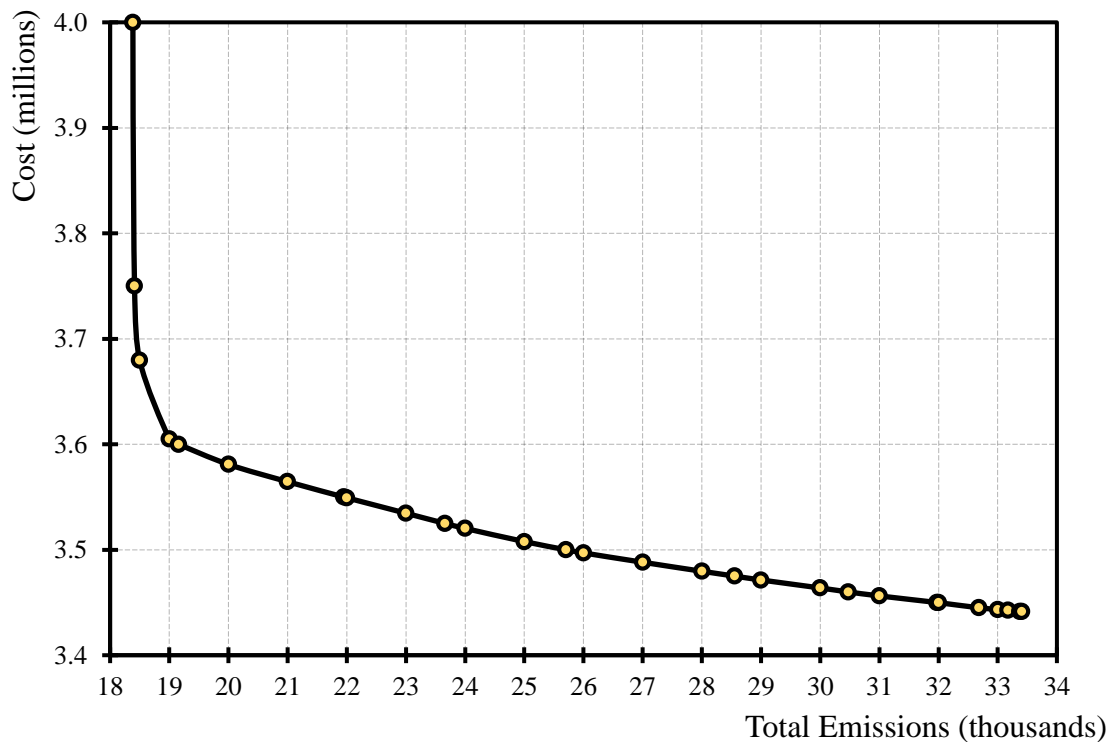


Figure 5-19 Total emissions reduction and cost increase under different emissions caps (with respect to the emissions unconstrained case, i.e., Case A)



**Figure 5-20 Multi-objective optimisation: Pareto frontier for total emissions and cost**

Finally, the proposed optimisation model has been used in a multi-objective optimisation framework through the  $\epsilon$ -constraint method. Total emissions and costs are the two objectives considered. Figure 5-20 displays the Pareto frontier found. The Pareto frontier shows clearly the trade-offs between the two conflicting objectives. Notice that any solution point: (i) below this Pareto frontier would be infeasible, and (ii) above this Pareto frontier is suboptimal. Figure 5-20 shows that the total cost grows exponentially to achieve reduction in total emissions below 19,000 metric units. In practice, a decision maker would most probably select a solution point within the second interval of the x-axis of Figure 5-20 (i.e., total emissions from 19,000 to 20,000 metric units).

## 5.8 Conclusions

In this study, the Energy State Task Network (E-STN) representation has been introduced as a means for modelling the main operations in material and energy supply chain networks in a unified fashion for design and planning problems of

such systems. The illustrative cases presented demonstrate the main features and the applicability of the general optimisation framework developed for techno-economic and environmental analysis studies. The case studies solved demonstrated that a more efficient way for emissions reductions is through regulation and emissions caps rather than increased emissions costs; a reduction of 3.3% in emissions has been reported. It has been shown how the proposed model can be used effectively to study the trade-off between costs and emissions levels and different environmental policies (i.e., emissions costs and caps) under sensitivity analysis and multi-objective optimisation studies. The proposed optimisation framework could be used to integrate various types of material and energy supply chain operations using a unified modelling representation. Overall, the proposed design and planning model can address an extensive range of energy supply chain networks. Introduction of problem-specific constraints may be required in some cases.



## **6 OVERALL DISCUSSIONS, GENERAL CONCLUSIONS AND RECOMMENDATION**

### **6.1 Overall Discussions**

In this PhD research, the applicability of the proposed optimisation-based approach for the planning of production and utility systems in process industries is presented with the main purpose of reducing energy needs, material resources utilisation and total costs of the overall system. The proposed optimisation framework considers for utility and production units: (i) unit commitment constraints; (ii) unit performance degradation and recovery model; (iii) different cleaning policies; (iv) alternative cleaning tasks options; (v) limited availability of cleaning resources; (vi) the initial state of the overall system at the beginning of each planning horizon; and (vii) terminal constraints at the end of the planning horizon. To the best of my knowledge, this is the first PhD research on the integrated optimisation-based model for the planning of production and utility systems by considering all of these operational and maintenance aspects (refer to Chapter 2, 3 and 4). The key findings showed that the total cost of the solution of the integrated approach was lower than that of the solution of the sequential approach within a range of 5% to 32% (refer to Figure 2-13, Figure 2-27 and Figure 2-34). The reduction in total costs of the integrated approach has clearly shown the superiority of the solution derived from the proposed integrated approach than that of the poor solution of traditional sequential approach. It has also been demonstrated that the proposed integrated approach can result in an enhanced energy efficiency of the overall system through more efficient operation of utility systems (i.e., unnecessary purchases of utility resources can be avoided) and the improved utilisation of energy and material resources (i.e., the Gantt chart of the optimal operational and cleaning plan as shown in Figure 2-7, Figure 3-5, Figure 4-4).

Furthermore, the proposed integrated optimisation-based model was further improved with the presence of process uncertainty in order to address dynamic production environment in the process industries. There were two significant

contributions to knowledge on the proposed integrated optimisation-based model under process uncertainties (refer to Chapter 2 and 4). In the first work, the optimisation framework followed a reactive planning approach through a rolling horizon representation to readily deal with certain types of uncertainties such as process-inherent uncertainty (e.g., level of inventory tanks), discrete uncertainty (e.g., startup and shutdown history of units), and external uncertainty (e.g., the demands for products). In the second work, the method of two-stage stochastic programming model under different scenarios of product demand uncertainty was used. Moreover, the stochastic programming model followed a rolling-horizon modelling representation that resulted to a hybrid reactive-proactive planning approach. The aggregated total cost of rolling horizon stochastic programming solution was 48% higher than that of the perfect information solution (refer to Figure 4-18). Notice that, the perfect information solution is difficult to be found due to uncertainties in the planning of production and utility systems in process industries. In addition, the generation of final optimal plan from these two research works demonstrated that the operational and cleaning plan of the current prediction horizon was updated accordingly after each iteration (refer to Figure 2-28 and Figure 4-12). These results show that the process uncertainties should be incorporated in the proposed optimisation framework in order to closely represent the real-industrial planning problems of production and utility systems.

However, integrated planning problems of production and utility system in process industries results to large MIP model that is difficult to solve to optimality and computationally time-consuming. The integrated approach may not be the most appropriate approach for solving real-industrial planning problems due to this reason. With this regards, three-stage MIP-based decomposition strategy was proposed for efficient scheduling of multistage production system and CHP-based utility system (refer to Chapter 3). The computational experiments showed that the solutions of the proposed MIP-based decomposition strategy can achieve optimal solutions within maximum predefined time limit (refer to Table 3-11). In addition, the computational time of the proposed decomposition strategy was faster than that of the integrated approach by an average magnitude of 4. These

results show that the three-stage MIP-based decomposition strategy can be an intermediary approach with the combined benefits of fast computational time of sequential approach and greater profitability offered by the integrated approach.

This PhD research also includes an additional research on the unified modelling representation for the design and planning problems in material and energy supply chain networks (refer to Chapter 5). The efficient management of supply chain network in energy-intensive process industries is an important upper level decision-making for improving energy efficiency and securing energy resources for its long-term sustainable operation. The benefits of the proposed unified modelling representation for the design and planning of material and energy supply chain networks can address an extensive range of energy supply chain networks (e.g., oil and gas industries, power industries, and renewable energy industries). From the solutions of the case studies, only a small reduction of emissions was observed by increased emissions costs (refer to Figure 5-14). Meanwhile, a reduction of 3.3% in emissions was achieved by imposing emissions caps (refer to Figure 5-16). The key result of this research work demonstrates that a more efficient way for emissions reductions is through the execution of emissions caps by regulations rather than increased emissions costs.

## **6.2 Novelty**

The novelty that can be derived from the intellectual contribution of PhD research findings is on the applicability and salient features of the proposed integrated optimisation-based approach as described in the following: (i) the enhanced energy efficiency of the overall system through significant reduction in total costs and energy needs from external sources; (ii) the proposed integrated approach results in a cleaner production since energy generation and consumption along with cleaning operations plans are simultaneously optimised; (iii) the applicability of the production and cleaning planning optimisation approach is further enhanced by integrating with decomposition strategy to achieve optimal or near optimal solutions at relatively low computational time; (iv) the proposed

optimisation model is improved with the presence of uncertainty in order to address dynamic production environment; and (v) economic and environmental benefits of the proposed integrated optimisation-based model shows a reduction in emissions by imposing emissions caps with moderate cost increase.

Finally, the potential impacts of the PhD research findings focus on the opportunity to transform the traditional planning of process industries to enhanced planning of process industries where all operations and maintenance aspects are performed simultaneously in order to achieve better economic and environmental performance. In addition, the proposed approach can provide a substantial support to the decision makers in energy-intensive process industries since the derived optimal solutions can obtain the detailed optimal plan of the overall systems and also relevant optimal profiles such as operational level profiles, performance degradation profiles and inventory level profiles.

### **6.3 General Conclusions**

In this PhD thesis, a general optimization framework for the simultaneous operational and maintenance planning of utility and production systems has been developed to include: (i) relevant operational and maintenance aspects (i.e., Chapter 2, 3 and 4); (ii) incorporation of uncertainties (i.e., Chapter 2 and 4); and (iii) development of decomposition strategy for effective planning solutions (i.e., Chapter 3). Moreover, additional work is presented for the design and planning of energy supply chain networks that can be applied to a wide range of supply chain networks such as supply chain management in process industries to ensure its long-term sustainable operations (i.e., Chapter 5).

The aim of this PhD research was achieved by a number of representative case studies in order to show the applicability and major benefits of the integrated planning of production and utility systems such as: (i) efficient energy and material resources utilisation (i.e., no unnecessary purchases of resources is presented due to more efficient operation of utility systems as previously discussed in Figure 2-34); (ii) overall cost reduction (i.e., total cost of the solution of the integrated approach is lower than the solution of the sequential approach

within a range of 5% to 32% as shown in Figure 2-27 and Figure 2-34); (iii) dealing with process uncertainties (i.e., generation of actual operational and cleaning planning as displayed in Figure 2-28 and Figure 4-12); (iv) emissions reduction potential (i.e., selection of fuels with lower emissions coefficient for the operation of boilers as demonstrated in Figure 3-8); and (v) effective solution approach through the use of decomposition strategy (i.e., the computational time of decomposition strategy is faster than that of the integrated approach by an average magnitude of 4 as briefly discussed for Table 3-11).

This aim has been successfully accomplished through the realization of the following research objectives:

1. Research background and literature review for each chapter to identify the current status of operational and maintenance planning for the process industry (Objective 1).
2. Optimisation-based approach was developed as MILP model for optimal operational and cleaning planning for the process industry (Objective 2).
3. The reactive and proactive planning approaches such as rolling horizon optimisation framework, two-stage stochastic programming model and hybrid approach were used to further enhance the developed optimisation-based approach under process uncertainties (Objective 3).
4. Three-stage MIP-based decomposition strategy was proposed to enhance the applicability and the efficiency of the production and cleaning planning optimisation approach (Objective 4).
5. Comprehensive analysis such as cost comparison, computational experiments, sensitivity and multi-objective analysis were performed to demonstrate the major benefits of the integrated operational and cleaning planning of production and utility systems (Objective 5).

As a whole, the proposed optimisation-based approach has clearly demonstrated the important benefits of the integrated planning of production and utility systems by considering major operational and maintenance aspects under process uncertainties. In addition, one of the major steps for addressing industrial

scenarios is the modelling of more complex production processes along with the development of decomposition strategy for an effective solution of highly complicated planning problems.

## **6.4 Recommendation for Future Research**

The PhD research on the optimisation-based approach for simultaneous operational and maintenance planning in process industry is relatively new research area and there is considerable recommendation for further development. In the following, some recommendations for future research are highlighted:

### **1. Nonlinear process model**

Most existing works on the planning and scheduling used linear process (LP) model to represent a simplification of the realistic industrial operations. It is desirable to consider nonlinear process (NP) model especially for performance degradation model for process units that can be modelled effectively through the other condition-based monitoring techniques such as vibrations and noise levels in order to accurately predict failure rate or performance degradation rate of the process units. However, solving NP model may not guarantee optimal solutions. In addition large-scale planning problems are usually hard NP model which makes the problems more complicated. With this regards, some NP model can be linearised into LP model to solve the planning problems in a linear formulation (Pistikopoulos et al., 2001).

### **2. Other planning approaches under uncertainties**

The presence of uncertainties in the planning problems transform the original deterministic model to stochastic, parametric or robust model in order to produce feasible and practical schedules for the industrial operations. The other types of methodological approach for the planning model under uncertainties is multi-stage stochastic programming model (Balasubramanian and Grossmann, 2004), multi-parametric programming model (Kopanos and Pistikopoulos, 2014) and robust optimisation model (Lin, Janak and Floudas, 2004). It is appropriate to fully understand the

types of uncertainties that occurred in the industrial processes and the use of advanced approaches in order to closely represent the realistic industrial operations.

### 3. Demand side management

Demand side management (DSM) is also known as active management of electricity demand can be considered in the proposed optimisation model to efficiently evaluate the integrated management in process industries with consideration of electricity supply and demand and fluctuation of electricity prices that is based on current electricity markets. The purpose of considering DSM is to reduce electrical energy consumption by changing the amount and timing of the consumer's use of electricity (Merkert et al., 2015; Zhang and Grossmann, 2016).

### 4. Integration of optimisation and simulation models

The planning models do not involve complex constraints of process operations such as chemical and physical properties of the materials, thermodynamic equations and reaction correlations of the major process units. The integration of optimisation and simulation is necessary to obtain accurate optimal solutions while simultaneously predict the current operating conditions of the process operations (Allaoui and Artiba, 2004).

### 5. Graphical user interface (GUI)

There are great potential to incorporate the proposed optimisation model into the software that can support GUI to assist the end users (e.g., planners, engineers or managers) in industrial companies to visualise the best possible schedules and other operational profiles. The users do not need to deal with complex mathematical model since the planning problems are solved in the background of the software. The GUI can be very beneficial to visualise clearly the optimal results in the form of a Gantt chart and other relevant figures such as graphs and pie charts at an immediate time frame. The decision makers of the industrial companies can make the right decisions based on the current performances of their process operations. The study on the development of graphical user interface (GUI) for the planning of production and utility system is initiated

by Tsigkaris (2017). He used AIMMS, a type of optimization software with powerful visualisation tools. This study is the first step towards the automated planning and management with comprehensive visualisation features and simplified interfaces so as to deliver more user-friendly experience to the end users. Other types of software such as Visual Studio and Python can be used to build an advanced GUI.



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# APPENDICES

## Appendix A OPTIMIZATION CODING IN GAMS

This appendix shows equations coding in GAMS for all corresponding chapters. The full version of the overall optimisation coding can be obtained in Cranfield Online Research Data (CORD).

### A.1 Chapter 2

#### A.1.1 Case study 1 and 2 (Integrated Approach)

```
*=====
*===== STARTUP and SHUTDOWN =====
*=====
EQUATIONS          SFX1,SFX2,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0;

SFX1(i,t)$(KE(i) AND I_SF(i) AND PH(t))..
    S(i,t) - F(i,t) =E= X(i,t) - xip(i)$(ORD(t)=1) - X(i,t-1)$(ORD(t)>1);
SFX2(i,t)$(KE(i) AND I_SF(i) AND PH(t))..
    S(i,t) + F(i,t) =L= 1;
S_MIN(i,t)$(KE(i) AND I_SMIN(i) AND PH(t) AND omega(i)>1)..
    X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omega(i)+1)) AND
ORD(tt) LE ORD(tt)),S(i,tt));
S_MIN0(i,t)$(KE(i) AND I_SMIN(i) AND PH(t) AND (ORD(t) LE (omega(i)-omegap(i))) AND
(omegap(i)>0 AND omegap(i)<omega(i)))..
    X(i,t) =E= 1;
F_MIN(i,t)$(KE(i) AND I_FMIN(i) AND PH(t) AND psi(i)>1)..
    1 - X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-psi(i)+1))
AND ORD(tt) LE ORD(tt)),F(i,tt));
F_MIN0(i,t)$(KE(i) AND I_FMIN(i) AND PH(t) AND (ORD(t) LE (psi(i)-psip(i))) AND
(psip(i)>0 AND psip(i)<psi(i)))..
    X(i,t) =E= 0;
X_MAX1(i,t)$(KE(i) AND MR(i) AND PH(t))..
    SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omikron(i))) AND ORD(tt) LE
ORD(tt)),X(i,tt)) =L= omikron(i);
X_MAX0(i,t)$(KE(i) AND MR(i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1)) AND
(omegap(i)>1))..
    SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i)))) AND ORD(tt)
LE ORD(tt)),X(i,tt)) =L= (omikron(i)-omegap(i));
*=====
*===== PRODUCTION AND UTILITY SYSTEM =====
*=====
EQUATIONS          PROD_QS,PROD_LB,PROD_UB,PROD_Y,PROD_YX1,PROD_YX2, UT_QE,UT_LB,UT_UB,
InvUT_OUT,InvUT_LB,InvUT_UB, DEM_FP,DEM_UT;
PROD_QS(i,t)$(KE(i) AND PH(t) AND PR(i))..
    QS(i,t) =E= SUM(e$EI(i,e),QE(i,e,t));
PROD_LB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    QE(i,e,t) =G= qe_min(i,e,t)*Y(i,e,t);
PROD_UB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    QE(i,e,t) =L= qe_max(i,e,t)*Y(i,e,t);
PROD_Y(i,t)$(KE(i) AND PH(t) AND PR(i))..
    SUM(e$EI(i,e),Y(i,e,t)) =L= 1;
PROD_YX1(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    Y(i,e,t) =L= X(i,t);
PROD_YX2(i,t)$(KE(i) AND PH(t) AND PR(i))..
    X(i,t) =L= SUM(e$EI(i,e),Y(i,e,t));
UT_QE(i,e,t)$(KE(i) AND PH(t) AND UT(i) AND EI(i,e))..
    QE(i,e,t) =E= coef_e(i,e)*QS(i,t);
UT_LB(i,t)$(KE(i) AND PH(t) AND UT(i))..
    QS(i,t) =G= qs_min(i,t)*X(i,t);
UT_UB(i,t)$(KE(i) AND PH(t) AND UT(i))..
    QS(i,t) =L= qs_max(i,t)*X(i,t);
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Inv_IN(e,z,t)$(PH(t) AND ZE(z,e))..
      B_IN(e,z,t) =E= SUM(i$(KE(i) AND EI(i,e) AND ZI_IN(z,i)),QE(i,e,t));
InvIN_LB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
      B_IN(e,z,t) =G= bin_min(e,z,t);
InvIN_UB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
      B_IN(e,z,t) =L= bin_max(e,z,t);
Inv(e,z,t)$(PH(t) AND ZE(z,e))..
      B(e,z,t) =E= bitap(e,z)$(ORD(t)=1) + (1-bitaz(z))*B(e,z,t-1)$(ORD(t)>1)
+ B_IN(e,z,t) - B_OUT(e,z,t);
Inv_LB(e,z,t)$(PH(t) AND ZE(z,e))..
      B(e,z,t) =G= b_min(e,z);
Inv_UB(e,z,t)$(PH(t) AND ZE(z,e))..
      B(e,z,t) =L= b_max(e,z);
InvUT_OUT(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e))..
      B_OUT(e,z,t) =E= SUM(i$(KE(i) AND PR(i) AND ZI_OUT(z,i)),
BU_OUT(e,z,i,t));
InvUT_LB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
      B_OUT(e,z,t) =G= bout_min(e,z,t);
InvUT_UB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
      B_OUT(e,z,t) =L= bout_max(e,z,t);
DEM_FP(e,t)$(PH(t) AND E_PR(e))..
      SUM(z$ZE(z,e), B_OUT(e,z,t)) + NS_PR(e,t) =E= thita(e,t);
DEM_UT(e,i,t)$(KE(i) AND PH(t) AND E_UT(e) AND IE_PR(i,e))..
      NS_UT(e,i,t) + SUM(z$(ZE(z,e) AND ZI_OUT(z,i)), BU_OUT(e,z,i,t))
      =E= SUM(ee$(E_PR(ee) AND EI(i,ee)), alpha(i,ee,e)*QE(i,ee,t) +
bita(i,ee,e)*Y(i,ee,t));
*=====
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*=====
EQUATIONS      OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;

OFCL_DM(i,t)$(KE(i) AND PH(t) AND IDM(i,t))..
      X(i,t) =E= 0;
OFCL_FM(i,t)$(KE(i) AND IFM(i))..
      SUM((q,t)$(QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tls(i))), H(i,q,t)) =E= 1;
OFCL(i,q,t)$(KE(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))))..
      X(i,t) + SUM(tt$(PH(tt) AND (ORD(tt) GE max(tes(i), (ORD(t)-
ni_q(i,q)+1))) AND (ORD(tt) LE min(tls(i),ORD(t)))), H(i,q,tt)) =L= 1;
LinkWH(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE tls(i))))..
      W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RSOURCE(t)$(PH(t))..
* on-line condition-based cleaning
      SUM(i$(KE(i) AND IOM(i)), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
      + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND
(ORD(tt) GE (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
      + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i),ORD(t))),hres(i,q)*H(i,q,tt))
      =L= hita(t) - SUM(i$(KE(i) AND IDM(i,t)), hitap(i,t));
*=====
*===== DEGRADATION & RECOVERY PERFORMANCE MODEL =====
*=====
EQUATIONS      DEG1,DEG2,DEG3, RECM1,RECM2,RECM3, VX,CONOM,VP;

DEG1(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
      U(i,t) =L= deg_ub(i)*X(i,t);
DEG2(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
      U(i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*((qs_max(i,t)-
QS(i,t))/qs_max(i,t)) - deg_ub(i)*(1-X(i,t));
DEG3(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
      U(i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*((qs_max(i,t)-
QS(i,t))/qs_max(i,t)) + deg_ub(i)*(1-X(i,t));

RECM1(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i))..
      R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
      R(i,t) =G= (R(i,t-1)$(ORD(t)>1) + dsp(i)$(ORD(t)=1) + X(i,t)) -

```

```

bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECM3(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
      R(i,t) =G= (R(i,t-1)$ (ORD(t)>1) + dsp(i)$ (ORD(t)=1) + 1)*(1-recov(i)) -
bigM(i,t)*(1-V(i,t));
VX(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
      V(i,t) =L= X(i,t);
CONOM(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
      SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(t)-gap_on(i)+1),1)) AND
(ORD(tt) LE ORD(t))), V(i,tt)) =L= 1;
VP(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i)) AND ORD(t) LE (gap_on(i)-
gap_onp(i)))..
      V(i,t) =E= 0;

```

**EQUATION** OBJECTIVE;

```

OBJECTIVE..      OF =E= SUM((i,t)$ (KE(i) AND I_SF(i) AND PH(t)),
((cost_s(i,t)*S(i,t)+(cost_f(i,t)*F(i,t))))
      + SUM((i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
cost_qe(i,e,t)*QE(i,e,t) + cost_y(i,e,t)*Y(i,e,t))
      + SUM((i,t)$ (KE(i) AND PH(t) AND UT(i)), cost_qs(i,t)*QS(i,t) +
cost_x(i,t)*X(i,t))
      + SUM((e,t)$ (E_PR(e) AND PH(t)), cost_ns_p(e,t)*NS_PR(e,t))
      + SUM((e,i,t)$ (KE(i) AND PH(t) AND IE_PR(i,e)),
cost_ns_u(e,i,t)*NS_UT(e,i,t))
      + SUM((i,t)$ (KE(i) AND PH(t) AND ICBM(i)), cost_u(i,t)*U(i,t))
      + SUM((i,q,t)$ (KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),
cost_h(i,q,t)*H(i,q,t))
      + SUM((i,t)$ (KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*V(i,t));
=====

```

**MODEL** UTILITY\_PROD\_SYSTEM\_RH /all/;

## A.1.2 Case study 1 and 2 (Sequential Approach)

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=====
=====
===== STARTUP and SHUTDOWN =====
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EQUATIONS          SFX1,SFX2,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0;

SFX1(i,t)$ (KE(i) AND I_SF(i) AND PH(t))..
      S(i,t) - F(i,t) =E= X(i,t) - xip(i)$ (ORD(t)=t_first) - X(i,t-
1)$ (ORD(t)>t_first);
SFX2(i,t)$ (KE(i) AND I_SF(i) AND PH(t))..
      S(i,t) + F(i,t) =L= 1;
S_MIN(i,t)$ (KE(i) AND I_SMIN(i) AND PH(t) AND omega(i)>1)..
      X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omega(i)+1)) AND
ORD(tt) LE ORD(t)),S(i,tt));
S_MIN0(i,t)$ (KE(i) AND I_SMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+omega(i)-
omegap(i))) AND (omegap(i)>0 AND omegap(i)<omega(i)))..
      X(i,t) =E= 1;
F_MIN(i,t)$ (KE(i) AND I_FMIN(i) AND PH(t) AND psi(i)>1)..
      1 - X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-psi(i)+1))
AND ORD(tt) LE ORD(t)),F(i,tt));
F_MIN0(i,t)$ (KE(i) AND I_FMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+psi(i)-psip(i))
AND (psip(i)>0 AND psip(i)<psi(i)))..
      X(i,t) =E= 0;
X_MAX1(i,t)$ (KE(i) AND MR(i) AND PH(t))..
      SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omikron(i))) AND ORD(tt) LE
ORD(t)),X(i,tt))
      =L= omikron(i);
X_MAX0(i,t)$ (KE(i) AND MR(i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1)) AND
(omegap(i)>1))..
      SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i))))
AND ORD(tt) LE ORD(t)),X(i,tt))
      =L= (omikron(i)-omegap(i));

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===== PRODUCTION AND UTILITY SYSTEM =====
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EQUATIONS          PROD_LB,PROD_UB,PROD_Y,PROD_YX1,PROD_YX2, UT_QE,UT_LB,UT_UB,
Inv_IN,InvIN_LB,InvIN_UB, Inv,Inv_LB,Inv_UB,

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InvUT_OUT,InvUT_LB,InvUT_UB, DEM_FP,DEM_UT, DEM_SEQ;

PROD_LB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    QE(i,e,t) =G= qe_min(i,e,t)*Y(i,e,t);
PROD_UB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    QE(i,e,t) =L= qe_max(i,e,t)*(Y(i,e,t) - q_red(i)*V(i,t));
PROD_Y(i,t)$(KE(i) AND PH(t) AND PR(i))..
    SUM(e$EI(i,e),Y(i,e,t)) =L= 1;
PROD_YX1(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    Y(i,e,t) =L= X(i,t);
PROD_YX2(i,t)$(KE(i) AND PH(t) AND PR(i))..
    X(i,t) =L= SUM(e$EI(i,e),Y(i,e,t));
UT_QE(i,e,t)$(KE(i) AND PH(t) AND UT(i) AND EI(i,e))..
    QE(i,e,t) =E= coef_e(i,e)*QS(i,t);
UT_LB(i,t)$(KE(i) AND PH(t) AND UT(i))..
    QS(i,t) =G= qs_min(i,t)*X(i,t);
UT_UB(i,t)$(KE(i) AND PH(t) AND UT(i))..
    QS(i,t) =L= qs_max(i,t)*(X(i,t)- q_red(i)*V(i,t));
Inv_IN(e,z,t)$(PH(t) AND ZE(z,e))..
    B_IN(e,z,t) =E= SUM(i$(KE(i) AND EI(i,e) AND ZI_IN(z,i)),QE(i,e,t));
InvIN_LB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(e,z,t) =G= bin_min(e,z,t);
InvIN_UB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(e,z,t) =L= bin_max(e,z,t);
Inv(e,z,t)$(PH(t) AND ZE(z,e))..
    B(e,z,t) =E= bitap(e,z)$(ORD(t)=t_first) + (1-bitaz(z))*B(e,z,t-
1)$(ORD(t)>t_first) + B_IN(e,z,t)- B_OUT(e,z,t);
Inv_LB(e,z,t)$(PH(t) AND ZE(z,e))..
    B(e,z,t) =G= b_min(e,z);
Inv_UB(e,z,t)$(PH(t) AND ZE(z,e))..
    B(e,z,t) =L= b_max(e,z);
InvUT_OUT(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e))..
    B_OUT(e,z,t) =E= SUM(i$(KE(i) AND PR(i) AND ZI_OUT(z,i)),
BU_OUT(e,z,i,t));
InvUT_LB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(e,z,t) =G= bout_min(e,z,t);
InvUT_UB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(e,z,t) =L= bout_max(e,z,t);
DEM_FP(e,t)$(PH(t) AND E_PR(e))..
    SUM(z$ZE(z,e), B_OUT(e,z,t)) + NS_PR(e,t) =E= thita(e,t);
DEM_UT(e,i,t)$(KE(i) AND PH(t) AND E_UT(e) AND IE_PR(i,e) AND PROD_PLAN=0)..
    NS_UT(e,i,t) + SUM(z$(ZE(z,e) AND ZI_OUT(z,i)), BU_OUT(e,z,i,t))
    =E= SUM(ee$(E_PR(ee) AND EI(i,ee)), alpha(i,ee,e)*QE(i,ee,t)
+bita(i,ee,e)*Y(i,ee,t));
DEM_SEQ(e,t)$(PH(t) AND E_UT(e) AND PROD_PLAN=1)..
    SUM((i,ee)$(E_PR(ee) AND EI(i,ee) AND IE_PR(i,e)),
alpha(i,ee,e)*QE(i,ee,t) + bita(i,ee,e)*Y(i,ee,t)) =L= max_avail_e(e,t);
*====
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*====

EQUATIONS      OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;

OFCL_DM(i,t)$(KE(i) AND PH(t) AND IDM(i,t))..
    X(i,t) =E= 0;
OFCL_FM(i)$(KE(i) AND IFM(i))..
    SUM((q,t)$(QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tls(i))), H(i,q,t)) =E= 1;
OFCL(i,q,t)$(KE(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))))..
    X(i,t) + SUM(tt$(PH(tt) AND (ORD(tt) GE max(tes(i), (ORD(t)-
ni_q(i,q)+1))) AND (ORD(tt) LE min(tls(i),ORD(t))))) , H(i,q,tt)) =L= 1;
LinkWH(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE tls(i))))..
    W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RSOURCE(t)$(PH(t))..
* On-line condition-based cleaning
    SUM(i$(KE(i) AND IOM(i)), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND
(ORD(tt) GE (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1)))

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AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i), ORD(t))), hres(i,q)*H(i,q,tt))
=L= hita(t)- SUM(i$(KE(i) AND IDM(i,t)), hitap(i,t));
*=====
*----- DEGRADATION & RECOVERY PERFORMANCE MODEL -----
*=====
EQUATIONS      DEG1, DEG2, DEG3, RECM1, RECM2, RECM2_UB, RECMV, DQ1, DQ2, DQ2_UB, DQ3,
DQ2_PR, DQ3_PR, DQV_PR, VX, CONOM, VP;

DEG1(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
U(i,t) =L= deg_ub(i)*X(i,t);
DEG2(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
U(i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) - deg_ub(i)*(1-X(i,t));
DEG3(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
U(i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) + deg_ub(i)*(1-X(i,t));
RECM1(i,t)$ (KE(i) AND PH(t) AND IOFF_CB(i))..
R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t)) - bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECMV(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
1)*(1-recov(i)) - bigM(i,t)*(1-V(i,t));
RECM2_UB(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
R(i,t) =L= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t)) + bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ1(i,t)$ (KE(i) AND PH(t) AND IOFF_CB(i))..
DQ(i,t) =L= bigM(i,t)*(1-W(i,t));
DQ2(i,t)$ (KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qs_max(i,t)-QS(i,t))/qs_max(i,t))) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) -
1000*(1-X(i,t));
DQ3(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND UT(i))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qs_max(i,t)-QS(i,t))/qs_max(i,t)))*(1-recov(i)) - 1000*(1-V(i,t));
DQ2_UB(i,t)$ (KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
DQ(i,t) =L= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qs_max(i,t)-QS(i,t))/qs_max(i,t))) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) +
1000*(1-X(i,t));
DQ2_PR(i,e,t)$ (KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t))) - 1000*(W(i,t)$IOFF_CB(i) +
V(i,t)$IOM(i)) - deg_ub(i)*(1-Y(i,e,t));
DQ3_PR(i,e,t)$ (KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
DQ(i,t) =L= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t))) - 1000*(W(i,t)$IOFF_CB(i) +
V(i,t)$IOM(i)) + deg_ub(i)*(1-Y(i,e,t));
DQV_PR(i,e,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t)))*(1-recov(i)) - 1000*(1-V(i,t));
VX(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
V(i,t) =L= X(i,t);
CONOM(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(t)-gap_on(i)+1), t_first) AND (ORD(tt) LE
ORD(t))), V(i,tt)) =L= 1;
VP(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i) AND ORD(t) LE (t_first-
1+gap_on(i)-gap_onp(i))))..
V(i,t) =E= 0;
*=====
*-----
EQUATION OBJECTIVE;

OBJECTIVE.. OF =E= SUM((i,t)$ (KE(i) AND I_SF(i) AND
PH(t)), ((cost_s(i,t)*S(i,t)+(cost_f(i,t)*F(i,t))))
+ SUM((i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e)), cost_qe(i,e,t)*QE(i,e,t)
+ cost_y(i,e,t)*Y(i,e,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND UT(i)), cost_qs(i,t)*QS(i,t) + cost_x(i,t)*X(i,t))
+ SUM((e,t)$ (E_PR(e) AND PH(t)), cost_ns_p(e,t)*NS_PR(e,t))
+ SUM((e,i,t)$ (KE(i) AND PH(t) AND IE_PR(i,e)), cost_ns_u(e,i,t)*NS_UT(e,i,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND ICBM(i)), cost_u(i,t)*U(i,t))
+ SUM((i,q,t)$ (KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND
QI(i,q)), cost_h(i,q,t)*H(i,q,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*V(i,t));

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*=====
MODEL UTILITY_PROD_SYSTEM_RH /all/;

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### A.1.3 Case study 3 (Rolling Horizon Integrated Approach)

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*=====
*===== STARTUP and SHUTDOWN =====
*=====
EQUATIONS          SFX1,SFX2,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0;

SFX1(i,t)$(KE(i) AND I_SF(i) AND PH(t))..
    S(i,t) - F(i,t) =E= X(i,t) - xip(i)$ (ORD(t)=t_first) - X(i,t-1)$ (ORD(t)>t_first);
SFX2(i,t)$(KE(i) AND I_SF(i) AND PH(t))..
    S(i,t) + F(i,t) =L= 1;
S_MIN(i,t)$(KE(i) AND I_SMIN(i) AND PH(t) AND omega(i)>1)..
    X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omega(i)+1)) AND ORD(tt)
    LE ORD(tt)),S(i,tt));
S_MIN0(i,t)$(KE(i) AND I_SMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+omega(i)-
omegap(i))) AND (omegap(i)>0 AND omegap(i)<omega(i)))..
    X(i,t) =E= 1;
F_MIN(i,t)$(KE(i) AND I_FMIN(i) AND PH(t) AND psi(i)>1)..
    1 - X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-psi(i)+1)) AND ORD(tt)
    LE ORD(tt)),F(i,tt));
F_MIN0(i,t)$(KE(i) AND I_FMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+psi(i)-psip(i))
AND (psip(i)>0 AND psip(i)<psi(i)))..
    X(i,t) =E= 0;
X_MAX1(i,t)$(KE(i) AND MR(i) AND PH(t))..
    SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omikron(i))) AND ORD(tt) LE
    ORD(tt)),X(i,tt))=L= omikron(i);
X_MAX0(i,t)$(KE(i) AND MR(i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1)) AND
(omegap(i)>1))..
    SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i)))) AND ORD(tt)
    LE ORD(tt)),X(i,tt)) =L= (omikron(i)-omegap(i));
*=====
*===== PRODUCTION AND UTILITY SYSTEM =====
*=====
EQUATIONS          PROD_LB,PROD_UB,PROD_Y,PROD_YX1,PROD_YX2,UT_QE,UT_LB,UT_UB,
Inv_IN,InvIN_LB,InvIN_UB,Inv,Inv_LB,Inv_UB,InvUT_OUT,InvUT_LB,InvUT_UB,DEM_FP,DEM_UT;

PROD_LB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    QE(i,e,t) =G= qe_min(i,e,t)*Y(i,e,t);
PROD_UB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    QE(i,e,t) =L= qe_max(i,e,t)*(Y(i,e,t) - (q_red(i)*VE(i,e,t))$IOM(i));
PROD_Y(i,t)$(KE(i) AND PH(t) AND PR(i))..
    SUM(e$EI(i,e),Y(i,e,t)) =L= 1;
PROD_YX1(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
    Y(i,e,t) =L= X(i,t);
PROD_YX2(i,t)$(KE(i) AND PH(t) AND PR(i))..
    X(i,t) =L= SUM(e$EI(i,e),Y(i,e,t));
UT_QE(i,e,t)$(KE(i) AND PH(t) AND UT(i) AND EI(i,e))..
    QE(i,e,t) =E= coef_e(i,e)*QS(i,t);
UT_LB(i,t)$(KE(i) AND PH(t) AND UT(i))..
    QS(i,t) =G= qs_min(i,t)*X(i,t);
UT_UB(i,t)$(KE(i) AND PH(t) AND UT(i))..
    QS(i,t) =L= qs_max(i,t)*(X(i,t) - (q_red(i)*V(i,t))$IOM(i));
Inv_IN(e,z,t)$(PH(t) AND ZE(z,e))..
    B_IN(e,z,t) =E= SUM(i$(KE(i) AND EI(i,e) AND ZI_IN(z,i)),QE(i,e,t));
InvIN_LB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(e,z,t) =G= bin_min(e,z,t);
InvIN_UB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(e,z,t) =L= bin_max(e,z,t);
Inv(e,z,t)$(PH(t) AND ZE(z,e))..
    B(e,z,t) =E= bitap(e,z)$ (ORD(t)=t_first) + (1-bitaz(z))*B(e,z,t-
1)$ (ORD(t)>t_first) + B_IN(e,z,t) - B_OUT(e,z,t);
Inv_LB(e,z,t)$(PH(t) AND ZE(z,e))..
    B(e,z,t) =G= b_min(e,z);
Inv_UB(e,z,t)$(PH(t) AND ZE(z,e))..
    B(e,z,t) =L= b_max(e,z);
InvUT_OUT(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e))..
    B_OUT(e,z,t) =E= SUM(i$(KE(i) AND PR(i) AND ZI_OUT(z,i)),

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BU_OUT(e,z,i,t);
InvUT_LB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(e,z,t) =G= bout_min(e,z,t);
InvUT_UB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(e,z,t) =L= bout_max(e,z,t);
DEM_FP(e,t)$(PH(t) AND E_PR(e))..
    SUM(z$ZE(z,e), B_OUT(e,z,t)) + NS_PR(e,t) =E= thita(e,t);
DEM_UT(e,i,t)$(KE(i) AND PH(t) AND E_UT(e) AND IE_PR(i,e))..
    NS_UT(e,i,t) + SUM(z$(ZE(z,e) AND ZI_OUT(z,i)), BU_OUT(e,z,i,t))
    =E= SUM(ee$(E_PR(ee) AND EI(i,ee)), alpha(i,ee,e)*QE(i,ee,t) +
bita(i,ee,e)*Y(i,ee,t));
*=====
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*=====
EQUATIONS    OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;

OFCL_DM(i,t)$(KE(i) AND PH(t) AND IDM(i,t))..
    X(i,t) =E= 0;
OFCL_FM(i,t)$(KE(i) AND IFM(i))..
    SUM((q,t)$(QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE tls(i))),
    H(i,q,t)) =E= 1;
OFCL(i,q,t)$(KE(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE
tes(i) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1)))))..
    X(i,t) + SUM(tt$(PH(tt) AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND
(ORD(tt) LE min(tls(i),ORD(t))))), H(i,q,tt)) =L= 1;
LinkWH(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE tls(i)))).. W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RSOURCE(t)$PH(t)..
* on-line condition-based cleaning
    SUM(i$(KE(i) AND IOM(i)), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND
(ORD(tt) GE (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE
tes(i) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i),ORD(t))))),hres(i,q)*H(i,q,tt))
    =L= hita(t) - SUM(i$(KE(i) AND IDM(i,t)), hitap(i,t));
*=====
*===== DEGRADATION & RECOVERY PERFORMANCE MODEL =====
*=====
EQUATIONS    DEG1,DEG2,DEG3, RECM1,RECM2,RECM2_UB,RECMV, DQ1,DQ2,DQ2_UB,DQ3,
DQ2_PR,DQ3_PR,DQV_PR, VX,CONOM,VP, VE01,VE02;

DEG1(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
    U(i,t) =L= deg_ub(i)*X(i,t);
DEG2(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
    U(i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) - deg_ub(i)*(1-X(i,t));
DEG3(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
    U(i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) + deg_ub(i)*(1-X(i,t));

RECM1(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i))..
    R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
    R(i,t) =G= (R(i,t-1)$(ORD(t)>t_first) + dsp(i)$(ORD(t)=t_first) + X(i,t)) -
    bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECMV(i,t)$(KE(i) AND PH(t) AND IOM(i))..
    R(i,t) =G= (R(i,t-1)$(ORD(t)>t_first) + dsp(i)$(ORD(t)=t_first) + 1)*(1-recov(i))
    - bigM(i,t)*(1-V(i,t));
RECM2_UB(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
    R(i,t) =L= (R(i,t-1)$(ORD(t)>t_first) + dsp(i)$(ORD(t)=t_first) + X(i,t)) +
    bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ1(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i))..
    DQ(i,t) =L= bigM(i,t)*(1-W(i,t));
DQ2(i,t)$(KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DQ(i,t) =G= (DQ(i,t-1)$(ORD(t)>t_first) + dqp(i)$(ORD(t)=t_first) +
    ((qs_max(i,t)-QS(i,t))/qs_max(i,t))) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) -
    1000*(1-X(i,t));
DQ3(i,t)$(KE(i) AND PH(t) AND IOM(i) AND UT(i))..
    DQ(i,t) =G= (DQ(i,t-1)$(ORD(t)>t_first) + dqp(i)$(ORD(t)=t_first) +
    ((qs_max(i,t)-QS(i,t))/qs_max(i,t)))*(1-recov(i)) - 1000*(1-V(i,t));

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DQ2_UB(i,t)$(KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
  DQ(i,t) =L= (DQ(i,t-1)$(ORD(t)>t_first) + dqp(i)$(ORD(t)=t_first) +
  ((qs_max(i,t)-QS(i,t))/qs_max(i,t))) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) +
  1000*(1-X(i,t));
DQ2_PR(i,e,t)$(KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
  DQ(i,t) =G= (DQ(i,t-1)$(ORD(t)>t_first) + dqp(i)$(ORD(t)=t_first) +
  ((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t))) - 1000*(W(i,t)$IOFF_CB(i) +
  V(i,t)$IOM(i)) - deg_ub(i)*(1-Y(i,e,t));
DQ3_PR(i,e,t)$(KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
  DQ(i,t) =L= (DQ(i,t-1)$(ORD(t)>t_first) + dqp(i)$(ORD(t)=t_first) +
  ((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t))) + 1000*(W(i,t)$IOFF_CB(i) +
  V(i,t)$IOM(i)) + deg_ub(i)*(1-Y(i,e,t));
DQV_PR(i,e,t)$(KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
  DQ(i,t) =G= (DQ(i,t-1)$(ORD(t)>t_first) + dqp(i)$(ORD(t)=t_first) +
  ((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t)))*(1-recov(i)) - 1000*(1-V(i,t)) -
  deg_ub(i)*(1-Y(i,e,t));
VX(i,t)$(KE(i) AND PH(t) AND IOM(i))..
  V(i,t) =L= X(i,t);
CONOM(i,t)$(KE(i) AND PH(t) AND IOM(i))..
  SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(t)-gap_on(i)+1),t_first) AND (ORD(tt) LE
  ORD(tt))), V(i,tt)) =L= 1;
VP(i,t)$(KE(i) AND PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i)) AND ORD(t) LE (t_first-
  1+gap_on(i)-gap_onp(i)))..
  V(i,t) =E= 0;
VE01(i,e,t)$(KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
  VE(i,e,t) =L= Y(i,e,t);
VE02(i,t)$(KE(i) AND PH(t) AND IOM(i) AND PR(i))..
  V(i,t) =E= SUM(e$EI(i,e),VE(i,e,t));
*=====
*=====
EQUATION OBJECTIVE;
OBJECTIVE.. OF =E= SUM((i,t)$(KE(i) AND I_SF(i) AND
PH(t)), ((cost_s(i,t)*S(i,t)+(cost_f(i,t)*F(i,t))))
+ SUM((i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e)), cost_qe(i,e,t)*QE(i,e,t)
+ cost_y(i,e,t)*Y(i,e,t))
+ SUM((i,t)$(KE(i) AND PH(t) AND UT(i)), cost_qs(i,t)*QS(i,t) + cost_x(i,t)*X(i,t))
+ SUM((e,t)$(E_PR(e) AND PH(t)), cost_ns_p(e,t)*NS_PR(e,t))
+ SUM((e,i,t)$(KE(i) AND PH(t) AND IE_PR(i,e)), cost_ns_u(e,i,t)*NS_UT(e,i,t))
+ SUM((i,t)$(KE(i) AND PH(t) AND ICBM(i)), cost_u(i,t)*U(i,t))
+ SUM((i,q,t)$(KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),
cost_h(i,q,t)*H(i,q,t))
+ SUM((i,t)$(KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*V(i,t));
*=====
MODEL UTILITY_PROD_SYSTEM_RH /all/;
*=====
=====
=====
SET      iter      /it1*it30/;
PARAMETERS
save_B(iter,e,z,t), save_X(iter,i,t), save_Y(iter,i,e,t), save_S(iter,i,t),
save_F(iter,i,t), save_W(iter,i,t),
save_H(iter,i,q,t), save_V(iter,i,t), save_VE(iter,i,e,t), save_B_OUT(iter,e,z,t),
save_B_IN(iter,e,z,t), save_BU_OUT(iter,e,z,i,t),
save_NS_UT(iter,e,i,t), save_NS_PR(iter,e,t), save_QS(iter,i,t), save_QE(iter,i,e,t), save_R
(iter,i,t), save_DQ(iter,i,t), save_U(iter,i,t), save_hres(iter,i,t), max_tres(i), counter,
step, max_iter, pred_hor, control_hor, total_hor, thita_it(iter,e,t), model_stat(iter),
CPUs(iter);
max_tres(i) = smax(q$(KE(i) AND QI(i,q)),ni_q(i,q));
total_hor      = 30;
pred_hor       = 15;
control_hor    = 1;
step           = control_hor;
max_iter       = total_hor;
save_B(iter,e,z,t)=0; save_X(iter,i,t)=0; save_R(iter,i,t)=0; save_V(iter,i,t)=0;
save_hres(iter,i,t)=0; save_DQ(iter,i,t)=0;

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thita_it(iter,e,t) = thita(e,t);

DISPLAY max_tres, step,max_iter, pred_hor,control_hor,total_hor;

*=====
PH(t) = NO;
FOR(counter=1 to max_iter by step,

*===== UPDATE OF PARAMETERS =====
    PH(t)$ORD(t) GE counter AND ORD(t) LE (counter + pred_hor - 1)) = YES;
    t_first = counter;

IF(counter>1,
    bitap(e,z) = SUM((iter,t)$ORD(iter)=(counter-1) AND ORD(t)=(counter-1)),
    save_B(iter,e,z,t) );
    xip(i)$KE(i) = SUM((iter,t)$ORD(iter)=(counter-1) AND ORD(t)=(counter-1)),
    save_X(iter,i,t) );
    dsp(i)$KE(i) AND ICBM(i) = SUM((iter,t)$ORD(iter)=(counter-1) AND
ORD(t)=(counter-1)), save_R(iter,i,t) );
    dqp(i)$KE(i) AND ICBM(i) = SUM((iter,t)$ORD(iter)=(counter-1) AND
ORD(t)=(counter-1)), save_DQ(iter,i,t) );
    omegap(i)$KE(i) = SUM((iter,t)$ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (omegap(i)*save_X(iter,i,t) + save_X(iter,i,t) );
    psip(i)$KE(i) = SUM((iter,t)$ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (psip(i)*(1-save_X(iter,i,t)) + (1-save_X(iter,i,t))) );
    gap_onp(i)$IOM(i) = SUM((iter,t)$ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (gap_onp(i)*(1-save_V(iter,i,t)) + (1-save_V(iter,i,t))) );
    hitap(i,t)$KE(i) AND ORD(t) GE counter AND ORD(t) LE (counter+max_tres(i)-1) =
SUM(iter$ORD(iter)=(counter-1) AND (SUM(tt$ORD(tt)=t_first-
1),save_hres(iter,i,tt)>0)), save_hres(iter,i,t) );

    IDM(i,t)$KE(i) AND ORD(t) GE counter AND hitap(i,t)>0) = YES;
    );
*=====

    U.up(i,t)$KE(i) AND ORD(t)=(pred_hor-control_hor+counter) = 0.50*deg_ub(i);
    B.lo(e,z,t)$ORD(t)=(pred_hor-control_hor+counter) =
    0.20*b_max(e,z);

SOLVE UTILITY_PROD_SYSTEM_RH using MIP minimizing OF;

    model_stat(iter)$ORD(iter)=counter) =
UTILITY_PROD_SYSTEM_RH.modelstat;
    CPUs(iter)$ORD(iter)=counter) = UTILITY_PROD_SYSTEM_RH.resusd;

*===== SAVE SOLUTION FOR THE CH OF THE CURRENT PH =====
    save_B(iter,e,z,t) $(ORD(iter)=counter AND ORD(t)=counter) = B.l(e,z,t);
    save_X(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = X.l(i,t);
    save_Y(iter,i,e,t) $(ORD(iter)=counter AND ORD(t)=counter) = Y.l(i,e,t);
    save_S(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = S.l(i,t);
    save_F(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = F.l(i,t);
    save_W(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = W.l(i,t);
    save_H(iter,i,q,t) $(ORD(iter)=counter AND ORD(t)=counter) = H.l(i,q,t);
    save_V(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = V.l(i,t);
    save_VE(iter,i,e,t) $(ORD(iter)=counter AND ORD(t)=counter) = VE.l(i,e,t);
    save_B_OUT(iter,e,z,t) $(ORD(iter)=counter AND ORD(t)=counter) =
    B_OUT.l(e,z,t);
    save_B_IN(iter,e,z,t) $(ORD(iter)=counter AND ORD(t)=counter) =
    B_IN.l(e,z,t);
    save_BU_OUT(iter,e,z,i,t)$(ORD(iter)=counter AND ORD(t)=counter) =
    BU_OUT.l(e,z,i,t);
    save_NS_UT(iter,e,i,t) $(ORD(iter)=counter AND ORD(t)=counter) =
    NS_UT.l(e,i,t);
    save_NS_PR(iter,e,t) $(ORD(iter)=counter AND ORD(t)=counter) = NS.PR.l(e,t);
    save_QS(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = QS.l(i,t);
    save_QE(iter,i,e,t) $(ORD(iter)=counter AND ORD(t)=counter) = QE.l(i,e,t);
    save_R(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = R.l(i,t);
    save_DQ(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = DQ.l(i,t);
    save_U(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = U.l(i,t);

    save_hres(iter,i,t)$(ORD(iter)=counter AND ORD(t) GE counter) = hitap(i,t)
    + SUM((q,tt)$KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND (ORD(tt) GE

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(ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t)),hres(i,q)*H.l(i,q,tt))
+ SUM((q,tt)$ (KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE (tls(i)+ni_q(i,q)-1)) AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1)))
AND (ORD(tt) LE min(tls(i), ORD(t))))),hres(i,q)*H.l(i,q,tt));
*=====

DISPLAY counter, PH,bitap,xip,dsp,omegap,psip,gap_onp,hitap,IDM,thita,
save_B,save_X,save_Y,save_S,save_F,save_W,save_H,

save_V,save_VE,save_B_OUT,save_B_IN,save_BU_OUT,save_NS_UT,save_NS_PR,save_QS,sav
e_QE,save_R,save_DQ,save_U, save_hres,thita_it;

DISPLAY model_stat,CPUs,OF.L,
B_IN.L,B_OUT.L,B.L,BU_OUT.L,QS.L,QE.L,NS_UT.L,NS_PR.L,U.l,R.l,DQ.l,
X.L,S.L,F.L,V.l,VE.l,W.L,H.L,Y.L,
KE,ICBM,IFM,IOM,IOFF_CB;

OPTION Clear=PH, Clear=hitap, Clear=IDM, Clear=B_IN,Clear=B_OUT, Clear=B,
Clear=BU_OUT, Clear=QS, Clear=QE,
Clear=NS_UT, Clear=NS_PR, Clear=U, Clear=R, Clear=DQ, Clear=X, Clear=S,
Clear=F, Clear=V, Clear=VE, Clear=W, Clear=H, Clear=Y;

);

PARAMETERS OBJ_RH(iter), OBJ_RH_TOTAL;

OBJ_RH(iter) = SUM((i,t)$ (KE(i) AND I_SF(i)),
((cost_s(i,t)*save_S(iter,i,t)+(cost_f(i,t)*save_F(iter,i,t))))
+ SUM((i,e,t)$ (KE(i) AND PR(i) AND EI(i,e)),
cost_qe(i,e,t)*save_QE(iter,i,e,t) + cost_y(i,e,t)*save_Y(iter,i,e,t)
+ SUM((i,t)$ (KE(i) AND UT(i)), cost_qs(i,t)*save_QS(iter,i,t) +
cost_x(i,t)*save_X(iter,i,t))
+ SUM((e,t)$ (E_PR(e)), cost_ns_p(e,t)*save_NS_PR(iter,e,t))
+ SUM((e,i,t)$ (KE(i) AND IE_PR(i,e)),
cost_ns_u(e,i,t)*save_NS_UT(iter,e,i,t))
+ SUM((i,t)$ (KE(i) AND ICBM(i)), cost_u(i,t)*save_U(iter,i,t))
+ SUM((i,q,t)$ (KE(i) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),
cost_h(i,q,t)*save_H(iter,i,q,t))
+ SUM((i,t)$ (KE(i) AND IOM(i)), cost_v(i,t)*save_V(iter,i,t));

OBJ_RH_TOTAL = SUM(iter, OBJ_RH(iter));

DISPLAY OBJ_RH, OBJ_RH_TOTAL;

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### A.1.4 Case study 3 (Rolling Horizon Sequential Approach)

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*=====
*===== STARTUP and SHUTDOWN =====
*=====
EQUATIONS SFX1,SFX2,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0;

SFX1(i,t)$ (KE(i) AND I_SF(i) AND PH(t))..
S(i,t) - F(i,t) =E= X(i,t) - xip(i)$ (ORD(t)=t_first) - X(i,t-
1)$ (ORD(t)>t_first);
SFX2(i,t)$ (KE(i) AND I_SF(i) AND PH(t))..
S(i,t) + F(i,t) =L= 1;
S_MIN(i,t)$ (KE(i) AND I_SMIN(i) AND PH(t) AND omega(i)>1)..
X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1, (ORD(t)-omega(i)+1)) AND
ORD(tt) LE ORD(t)),S(i,tt));
S_MIN0(i,t)$ (KE(i) AND I_SMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+omega(i)-
omegap(i)) AND (omegap(i)>0 AND omegap(i)<omega(i))))..
X(i,t) =E= 1;
F_MIN(i,t)$ (KE(i) AND I_FMIN(i) AND PH(t) AND psi(i)>1)..
1 - X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1, (ORD(t)-psi(i)+1))
AND ORD(tt) LE ORD(t)),F(i,tt));
F_MIN0(i,t)$ (KE(i) AND I_FMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+psi(i)-psip(i))
AND (psip(i)>0 AND psip(i)<psi(i))))..
X(i,t) =E= 0;
X_MAX1(i,t)$ (KE(i) AND MR(i) AND PH(t))..
SUM(tt$(PH(tt) AND ORD(tt) GE max(1, (ORD(t)-omikron(i))) AND ORD(tt) LE
ORD(t)),X(i,tt))

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=L= omikron(i);
X_MAX0(i,t)$(KE(i) AND MR(i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1)) AND
(omegap(i)>1))..
SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i))))
AND ORD(tt) LE ORD(t)),X(i,tt))
=L= (omikron(i)-omegap(i));
*===== PRODUCTION AND UTILITY SYSTEM =====
*=====
EQUATIONS PROD_LB,PROD_UB,PROD_Y,PROD_YX1,PROD_YX2, UT_QE,UT_LB,UT_UB,
Inv_IN,InvIN_LB,InvIN_UB, Inv,Inv_LB,Inv_UB,
InvUT_OUT,InvUT_LB,InvUT_UB, DEM_FP,DEM_UT, DEM_SEQ;
PROD_LB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
QE(i,e,t) =G= qe_min(i,e,t)*Y(i,e,t);
PROD_UB(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
QE(i,e,t) =L= qe_max(i,e,t)*(Y(i,e,t) - (q_red(i)*VE(i,e,t))$IOM(i));
PROD_Y(i,t)$(KE(i) AND PH(t) AND PR(i))..
SUM(e$EI(i,e),Y(i,e,t)) =L= 1;
PROD_YX1(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
Y(i,e,t) =L= X(i,t);
PROD_YX2(i,t)$(KE(i) AND PH(t) AND PR(i))..
X(i,t) =L= SUM(e$EI(i,e),Y(i,e,t));
UT_QE(i,e,t)$(KE(i) AND PH(t) AND UT(i) AND EI(i,e))..
QE(i,e,t) =E= coef_e(i,e)*QS(i,t);
UT_LB(i,t)$(KE(i) AND PH(t) AND UT(i))..
QS(i,t) =G= qs_min(i,t)*X(i,t);
UT_UB(i,t)$(KE(i) AND PH(t) AND UT(i))..
QS(i,t) =L= qs_max(i,t)*(X(i,t) - (q_red(i)*V(i,t))$IOM(i));
Inv_IN(e,z,t)$(PH(t) AND ZE(z,e))..
B_IN(e,z,t) =E= SUM(i$(KE(i) AND EI(i,e) AND ZI_IN(z,i)),QE(i,e,t));
InvIN_LB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
B_IN(e,z,t) =G= bin_min(e,z,t);
InvIN_UB(e,z,t)$(PH(t) AND ZE(z,e) AND bin_cons=1)..
B_IN(e,z,t) =L= bin_max(e,z,t);
Inv(e,z,t)$(PH(t) AND ZE(z,e))..
B(e,z,t) =E= bitap(e,z)$(ORD(t)=t_first) + (1-bitaz(z))*B(e,z,t-
1)$(ORD(t)>t_first) + B_IN(e,z,t) - B_OUT(e,z,t);
Inv_LB(e,z,t)$(PH(t) AND ZE(z,e))..
B(e,z,t) =G= b_min(e,z);
Inv_UB(e,z,t)$(PH(t) AND ZE(z,e))..
B(e,z,t) =L= b_max(e,z);
InvUT_OUT(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e))..
B_OUT(e,z,t) =E= SUM(i$(KE(i) AND PR(i) AND ZI_OUT(z,i)),
BU_OUT(e,z,i,t));
InvUT_LB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
B_OUT(e,z,t) =G= bout_min(e,z,t);
InvUT_UB(e,z,t)$(PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
B_OUT(e,z,t) =L= bout_max(e,z,t);
DEM_FP(e,t)$(PH(t) AND E_PR(e))..
SUM(z$ZE(z,e), B_OUT(e,z,t)) + NS_PR(e,t) =E= thita(e,t);
DEM_UT(e,i,t)$(KE(i) AND PH(t) AND E_UT(e) AND IE_PR(i,e) AND PROD_PLAN=0)..
NS_UT(e,i,t) + SUM(z$(ZE(z,e) AND ZI_OUT(z,i)), BU_OUT(e,z,i,t))
=E= SUM(ee$(E_PR(ee) AND EI(i,ee)), alpha(i,ee,e)*QE(i,ee,t) +
bita(i,ee,e)*Y(i,ee,t));
DEM_SEQ(e,t)$(PH(t) AND E_UT(e) AND PROD_PLAN=1)..
SUM((i,ee)$(E_PR(ee) AND EI(i,ee) AND IE_PR(i,e)),
alpha(i,ee,e)*QE(i,ee,t) + bita(i,ee,e)*Y(i,ee,t)) =L= max_avail_e(e,t);
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*=====
EQUATIONS OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;
OFCL_DM(i,t)$(KE(i) AND PH(t) AND IDM(i,t))..
X(i,t) =E= 0;
OFCL_FM(i)$(KE(i) AND IFM(i))..
SUM((q,t)$(QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tls(i))), H(i,q,t)) =E= 1;
OFCL(i,q,t)$(KE(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))))..
X(i,t) + SUM(tt$(PH(tt) AND (ORD(tt) GE max(tes(i),(ORD(t)-
ni_q(i,q)+1))) AND (ORD(tt) LE min(tls(i),ORD(t))), H(i,q,tt)) =L= 1;

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LinkWH(i,t)$ (KE(i) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE tls(i))))..
W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RESOURCE(t)$PH(t)..
* on-line condition-based cleaning
SUM(i$(KE(i) AND IOM(i)), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
+ SUM((i,q,tt)$ (KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND
(ORD(tt) GE (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
+ SUM((i,q,tt)$ (KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i),ORD(t))))),hres(i,q)*H(i,q,tt))
=L= hita(t)- SUM(i$(KE(i) AND IDM(i,t)), hitap(i,t));
*=====
*===== DEGRADATION & RECOVERY PERFORMANCE MODEL =====
*=====
EQUATIONS DEG1,DEG2,DEG3, RECM1,RECM2,RECM2_UB,RECMV, DQ1,DQ2,DQ2_UB,DQ3,
DQ2_PR,DQ3_PR,DQV_PR, VX,CONOM,VP, VE01,VE02;
DEG1(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
U(i,t) =L= deg_ub(i)*X(i,t);
DEG2(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
U(i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) - deg_ub(i)*(1-X(i,t));
DEG3(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
U(i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) + deg_ub(i)*(1-X(i,t));
RECM1(i,t)$ (KE(i) AND PH(t) AND IOFF_CB(i))..
R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t)) - bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECMV(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
1)*(1-recov(i)) - bigM(i,t)*(1-V(i,t));
RECM2_UB(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
R(i,t) =L= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t)) + bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ1(i,t)$ (KE(i) AND PH(t) AND IOFF_CB(i))..
DQ(i,t) =L= bigM(i,t)*(1-W(i,t));
DQ2(i,t)$ (KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qs_max(i,t)-QS(i,t))/qs_max(i,t))) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) -
1000*(1-X(i,t));
DQ3(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND UT(i))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qs_max(i,t)-QS(i,t))/qs_max(i,t)))*(1-recov(i)) - 1000*(1-V(i,t));
DQ2_UB(i,t)$ (KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
DQ(i,t) =L= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qs_max(i,t)-QS(i,t))/qs_max(i,t))) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) +
1000*(1-X(i,t));
DQ2_PR(i,e,t)$ (KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t))) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) -
deg_ub(i)*(1-Y(i,e,t));
DQ3_PR(i,e,t)$ (KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
DQ(i,t) =L= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t))) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i)) +
deg_ub(i)*(1-Y(i,e,t));
DQV_PR(i,e,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(i,e,t))/qe_max(i,e,t)))*(1-recov(i)) - 1000*(1-V(i,t)) -
deg_ub(i)*(1-Y(i,e,t));
VX(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
V(i,t) =L= X(i,t);
CONOM(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(t)-gap_on(i)+1),t_first)) AND
(ORD(tt) LE ORD(t))), V(i,tt)) =L= 1;
VP(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i)) AND ORD(t) LE (t_first-
1+gap_on(i)-gap_onp(i)))..
V(i,t) =E= 0;
VE01(i,e,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..

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VE(i,e,t) =L= Y(i,e,t);
VE02(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i))..
V(i,t) =E= SUM(e$EI(i,e),VE(i,e,t));
*=====
*=====
EQUATION OBJECTIVE;

OBJECTIVE.. OF =E= SUM((i,t)$ (KE(i) AND I_SF(i) AND PH(t)),
((cost_s(i,t)*S(i,t)+(cost_f(i,t)*F(i,t))))
+ SUM((i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
cost_qe(i,e,t)*QE(i,e,t) + cost_y(i,e,t)*Y(i,e,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND UT(i)), cost_qs(i,t)*QS(i,t) +
cost_x(i,t)*X(i,t))
+ SUM((e,t)$ (E_PR(e) AND PH(t)), cost_ns_p(e,t)*NS_PR(e,t))
+ SUM((e,i,t)$ (KE(i) AND PH(t) AND IE_PR(i,e)),
cost_ns_u(e,i,t)*NS_UT(e,i,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND ICBM(i)), cost_u(i,t)*U(i,t))
+ SUM((i,q,t)$ (KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),
cost_h(i,q,t)*H(i,q,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*V(i,t));
*=====
*=====
MODEL UTILITY_PROD_SYSTEM_RH /all/;
*=====
*=====
*=====
SET iter /it1*it30/;

PARAMETERS
save_B(iter,e,z,t), save_X(iter,i,t), save_Y(iter,i,e,t), save_S(iter,i,t),
save_F(iter,i,t), save_W(iter,i,t), save_H(iter,i,q,t),
save_V(iter,i,t), save_VE(iter,i,e,t), save_B_OUT(iter,e,z,t), save_B_IN(iter,e,z,t),
save_BU_OUT(iter,e,z,i,t), save_NS_UT(iter,e,i,t), save_NS_PR(iter,e,t),
save_QS(iter,i,t), save_QE(iter,i,e,t), save_R(iter,i,t), save_DQ(iter,i,t), save_U(iter,i,t)
), save_hres(iter,i,t), max_tres(i), counter, step, max_iter, pred_hor, control_hor,
total_hor, thita_it(iter,e,t), model_stat(iter), CPUs(iter);

max_tres(i) = smax(q$(KE(i) AND QI(i,q)),ni_q(i,q));

total_hor = 30;
pred_hor = 15;
control_hor = 1;

step = control_hor;
max_iter = total_hor;

save_B(iter,e,z,t)=0; save_X(iter,i,t)=0; save_R(iter,i,t)=0; save_DQ(iter,i,t)=0;
save_V(iter,i,t)=0; save_hres(iter,i,t)=0;

thita_it(iter,e,t) = thita(e,t);

DISPLAY max_tres, step,max_iter, pred_hor,control_hor,total_hor;

max_avail_e('e1',t) = 250;
max_avail_e('e2',t) = 680;

*=====
PH(t) = NO;
FOR(counter=1 to max_iter by step,

*===== UPDATE OF PARAMETERS =====
PH(t)$ (ORD(t) GE counter AND ORD(t) LE (counter + pred_hor - 1)) = YES;
t_first = counter;

IF(counter>1,
bitap(e,z) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-1)),
save_B(iter,e,z,t) );
xip(i)$KE(i) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-1)),
save_X(iter,i,t) );
dsp(i)$ (KE(i) AND ICBM(i)) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND
ORD(t)=(counter-1)), save_R(iter,i,t) );
dqp(i)$ (KE(i) AND ICBM(i)) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND
ORD(t)=(counter-1)), save_DQ(iter,i,t) );

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omegap(i)$KE(i) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (omegap(i)*save_X(iter,i,t) + save_X(iter,i,t)) );
psip(i)$KE(i) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (psip(i)*(1-save_X(iter,i,t)) + (1-save_X(iter,i,t))) );
gap_onp(i)$IOM(i) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (gap_onp(i)*(1-save_V(iter,i,t)) + (1-save_V(iter,i,t))) );
hitap(i,t)$ (KE(i) AND ORD(t) GE counter AND ORD(t) LE (counter+max_tres(i)-1)) =
SUM(iter$(ORD(iter)=(counter-1) AND (SUM(tt$(ORD(tt)=t_first-
1),save_hres(iter,i,tt))>0)), save_hres(iter,i,t) );
IDM(i,t)$ (KE(i) AND ORD(t) GE counter AND hitap(i,t)>0) = YES;
);
*=====
***** SEQUENTIAL APPROACH *****
*===== PRODUCTION PLANNING PROBLEM =====
PROD_PLAN = 1;
KE(i)$UT(i) = NO;          UT(i) = NO;

U.up(i,t)$ (KE(i) AND ORD(t)=(pred_hor-control_hor+counter)) = 0.50*deg_ub(i);
B.lo(e,z,t)$ (E_PR(e) AND ZE(z,e) AND ORD(t)=(pred_hor-control_hor+counter)) =
0.20*b_max(e,z);

SOLVE UTILITY_PROD_SYSTEM_RH using MIP minimizing OF;

DISPLAY UTILITY_PROD_SYSTEM_RH.resusd,OF.L,
B_IN.L,B_OUT.L,B.L,BU_OUT.L,QS.L,QE.L,NS_UT.L,NS_PR.L,U.l,R.l,
X.L,S.L,F.L,V.l,W.L,H.L,Y.L, KE,ICBM,IFM,IOM,IOFF_CB;
*=====
model_stat(iter)$ (ORD(iter)=counter) = UTILITY_PROD_SYSTEM_RH.modelstat;
CPUs(iter)$ (ORD(iter)=counter) = UTILITY_PROD_SYSTEM_RH.resusd;
NS_PR.fx(e,t)$E_PR(e) = NS_PR.l(e,t);
QE.fx(i,e,t)$PR(i) = QE.l(i,e,t);
Y.fx(i,e,t)$PR(i) = Y.l(i,e,t);
X.fx(i,t)$PR(i) = X.l(i,t);
H.fx(i,q,t)$PR(i) = H.l(i,q,t);
V.fx(i,t)$PR(i) = V.l(i,t);
VE.fx(i,e,t)$PR(i) = VE.l(i,e,t);
B.fx(e,z,t)$E_PR(e) = B.l(e,z,t);
B_OUT.fx(e,z,t)$E_PR(e) = B_OUT.l(e,z,t);
B_IN.fx(e,z,t)$E_PR(e) = B_IN.l(e,z,t);
*===== UTILITY PLANNING PROBLEM =====
PROD_PLAN = 0;
UT(i)$ (ORD(i) le 5) = YES;          KE(i)$UT(i) = YES;
U.up(i,t)$ (KE(i) AND ORD(t)=(pred_hor-control_hor+counter)) = 0.50*deg_ub(i);
B.lo(e,z,t)$ (ZE(z,e) AND ORD(t)=(pred_hor-control_hor+counter)) = 0.20*b_max(e,z);

SOLVE UTILITY_PROD_SYSTEM_RH using MIP minimizing OF;

DISPLAY UTILITY_PROD_SYSTEM_RH.resusd,OF.L,
B_IN.L,B_OUT.L,B.L,BU_OUT.L,QS.L,QE.L,NS_UT.L,NS_PR.L,U.l,R.l,
X.L,S.L,F.L,V.l,W.L,H.L,Y.L,
KE,ICBM,IFM,IOM,IOFF_CB;
*=====
model_stat(iter)$ (ORD(iter)=counter) = model_stat(iter) +
UTILITY_PROD_SYSTEM_RH.modelstat - 1;
CPUs(iter)$ (ORD(iter)=counter) = CPUs(iter) +
UTILITY_PROD_SYSTEM_RH.resusd;
*****
*===== SAVE SOLUTION FOR THE CH OF THE CURRENT PH =====
save_B(iter,e,z,t) $ (ORD(iter)=counter AND ORD(t)=counter) = B.l(e,z,t);
save_X(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = X.l(i,t);
save_Y(iter,i,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = Y.l(i,e,t);
save_S(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = S.l(i,t);
save_F(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = F.l(i,t);
save_W(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = W.l(i,t);
save_H(iter,i,q,t) $ (ORD(iter)=counter AND ORD(t)=counter) = H.l(i,q,t);
save_V(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = V.l(i,t);
save_VE(iter,i,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = VE.l(i,e,t);
save_B_OUT(iter,e,z,t) $ (ORD(iter)=counter AND ORD(t)=counter) =
B_OUT.l(e,z,t);
save_B_IN(iter,e,z,t) $ (ORD(iter)=counter AND ORD(t)=counter) =
B_IN.l(e,z,t);

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save_BU_OUT(iter,e,z,i,t)$(ORD(iter)=counter AND ORD(t)=counter)
=BU_OUT.l(e,z,i,t);
save_NS_UT(iter,e,i,t) $(ORD(iter)=counter AND ORD(t)=counter) =
NS_UT.l(e,i,t);
save_NS_PR(iter,e,t) $(ORD(iter)=counter AND ORD(t)=counter) = NS_PR.l(e,t);
save_QS(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = QS.l(i,t);
save_QE(iter,i,e,t) $(ORD(iter)=counter AND ORD(t)=counter) = QE.l(i,e,t);
save_R(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = R.l(i,t);
save_DQ(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = DQ.l(i,t);
save_U(iter,i,t) $(ORD(iter)=counter AND ORD(t)=counter) = U.l(i,t);
save_hres(iter,i,t)$(ORD(iter)=counter AND ORD(t) GE counter) = hitap(i,t)
+ SUM((q,tt)$(KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND (ORD(tt) GE
(ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H.l(i,q,tt))
+ SUM((q,tt)$(KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE (tls(i)+ni_q(i,q)-1))AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))
AND (ORD(tt) LE min(tls(i),ORD(t))))),hres(i,q)*H.l(i,q,tt));
*=====

DISPLAY counter, PH,bitap,xip,dsp,omegap,psip,gap_onp,hitap,IDM,thita,
save_B,save_X,save_Y,save_S,save_F,save_W,save_H,save_V,save_VE,save_B_OUT,save_B_IN,sav
e_BU_OUT,save_NS_UT,save_NS_PR,save_QS,save_QE,save_R,save_DQ,save_U,
save_hres,thita_it;
DISPLAY model_stat,CPU,OF.L,
B_IN.L,B_OUT.L,B.L,BU_OUT.L,QS.L,QE.L,NS_UT.L,NS_PR.L,U.l,R.l,DQ.l,
X.L,S.L,F.L,V.l,VE.l,W.L,H.L,Y.L,
KE,ICBM,IFM,IOM,IOFF_CB;
OPTION Clear=PH, Clear=hitap, Clear=IDM, Clear=B_IN,Clear=B_OUT, Clear=B,
Clear=BU_OUT, Clear=QS, Clear=QE,Clear=NS_UT, Clear=NS_PR, Clear=U, Clear=R, Clear=DQ,
Clear=X, Clear=S, Clear=F, Clear=V, Clear=VE, Clear=W, Clear=H, Clear=Y;
);

PARAMETERS OBJ_RH(iter),OBJ_RH_TOTAL, OBJ_RH_NS_unit(iter,e),
OBJ_RH_No_NS(iter),OBJ_RH_No_NS_TOTAL;

OBJ_RH(iter) = SUM((i,t)$(KE(i) AND I_SF(i)),
((cost_s(i,t)*save_S(iter,i,t)+(cost_f(i,t)*save_F(iter,i,t))))
+ SUM((i,e,t)$(KE(i) AND PR(i) AND EI(i,e)), cost_qe(i,e,t)*save_QE(iter,i,e,t))
+ cost_y(i,e,t)*save_Y(iter,i,e,t))
+ SUM((i,t)$(KE(i) AND UT(i)), cost_qs(i,t)*save_QS(iter,i,t) +
cost_x(i,t)*save_X(iter,i,t))
+ SUM((e,t)$(E_PR(e)), cost_ns_p(e,t)*save_NS_PR(iter,e,t))
+ SUM((e,i,t)$(KE(i) AND IE_PR(i,e)), cost_ns_u(e,i,t)*save_NS_UT(iter,e,i,t))
+ SUM((i,t)$(KE(i) AND ICBM(i)), cost_u(i,t)*save_U(iter,i,t))
+ SUM((i,q,t)$(KE(i) AND (IFM(i) OR IOFF_CB(i) AND QI(i,q))),
cost_h(i,q,t)*save_H(iter,i,q,t))
+ SUM((i,t)$(KE(i) AND IOM(i)), cost_v(i,t)*save_V(iter,i,t));

OBJ_RH_TOTAL = SUM(iter, OBJ_RH(iter));

OBJ_RH_NS_unit(iter,e) = SUM((t)$(E_PR(e)), save_NS_PR(iter,e,t)) + SUM((i,t)$(KE(i) AND
IE_PR(i,e)), save_NS_UT(iter,e,i,t));

OBJ_RH_No_NS(iter) = OBJ_RH(iter) - SUM((e,t)$(E_PR(e)),
cost_ns_p(e,t)*save_NS_PR(iter,e,t))- SUM((e,i,t)$(KE(i) AND IE_PR(i,e)),
cost_ns_u(e,i,t)*save_NS_UT(iter,e,i,t));

OBJ_RH_No_NS_TOTAL = SUM(iter, OBJ_RH_No_NS(iter));

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## A.2 Chapter 3

### A.2.1 Equations Coding

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*=====
*===== STARTUP and SHUTDOWN =====
*=====
EQUATIONS SFX1,SFX2,SFX3,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0,SFX4;
SFX1(e,i,t)$(PH(t) AND I_SF(e,i))..
S(e,i,t) - F(e,i,t) =E= X(e,i,t) - xip(i,e)$(ORD(t)=t_first) - X(e,i,t-
1)$(ORD(t)>t_first);
SFX2(e,i,t)$(PH(t) AND I_SF(e,i))..

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S(e,i,t) + F(e,i,t) =L= 1;
S_MIN(e,i,t)$(PH(t) AND I_SMIN(e,i) AND omega(i)>1)..
X(e,i,t)=G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omega(i)+1))
AND ORD(tt) LE ORD(t)),S(e,i,tt));
S_MIN0(i,t)$(PH(t) AND (UT_B(i) OR UT_T(i)) AND (ORD(t) LE (t_first-1+omega(i)-
omegap(i))) AND (omegap(i)>0 AND omegap(i)<omega(i)))..
SUM(e$I_SMIN(e,i),X(e,i,t)) =E= 1;
F_MIN(e,i,t)$(PH(t) AND I_FMIN(e,i) AND psi(i)>1)..
1 - X(e,i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-psi(i)+1))
AND ORD(tt) LE ORD(t)),F(e,i,tt));
F_MIN0(i,t)$(PH(t) AND (UT_B(i) OR UT_T(i)) AND (ORD(t) LE (t_first-1+psi(i)-psip(i)))
AND (psip(i)>0 AND psip(i)<psi(i)))..
SUM(e$I_FMIN(e,i),X(e,i,t)) =E= 0;
X_MAX1(e,i,t)$(MR(e,i) AND PH(t))..
SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omikron(i))) AND ORD(tt) LE
ORD(t)),X(e,i,tt))
=L= omikron(i);
X_MAX0(e,i,t)$(MR(e,i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1) AND
(omegap(i)>1))..
SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i))))
AND ORD(tt) LE ORD(t)),X(e,i,tt))
=L= (omikron(i)-omegap(i));
SFX3(i,t)$(PH(t) AND UT_B(i))..
SUM(e$E_FUEL(e),X(e,i,t)) =L= 1;
SFX4(i,t)$(PH(t) AND UT_B(i))..
SUM(e$E_FUEL(e),S(e,i,t)) =L= 1;
*=====
*===== UTILITY SYSTEM =====
*=====
EQUATIONS B_FUEL,FUEL_LB,FUEL_UB,CONS_A,SB_RESTART,EMISSIONS,
R1,R2,HP_TURBINE, EP_LB,
HPT_LB,HPT_UB,EL_TURBINE,MIX_HP,MIX_MP,MIX_LP,DEMAND_EL,OBJ,
HP_BOILER_UB,HP_BOILER_LB,HPB_LB_SS,HPB_UB_SS;
B_FUEL(e,i,t)$(E_FUEL(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t)=E= BS(e,i,t-1)$(ORD(t)>1) + bitap(e,i)$(ORD(t)=1) -
SUM(ii$UT_B(ii),FT(e,i,ii,t) + FS(e,ii,t));
FUEL_LB(e,i,t)$(E_FUEL(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t) =G= b_min(e,i);
FUEL_UB(e,i,t)$(E_FUEL(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t) =L= b_max(e,i);
CONS_A(e,i,t)$(E_FUEL(e) AND UT_B(i) AND PH(t))..
SUM(p$PS(p), A(e,i,p,t)) =E= X(e,i,t);
HP_BOILER_UB(e,i,p,t)$(E_FUEL(e) AND UT_B(i) AND PS(p) AND PH(t))..
SUM(ii$ZE(ii,e),FT(e,ii,i,t)) =L= ft_min(e,i,p) +
rhop(e,i,p)*(QB(e,i,t) - qbp_min(e,i,p)) + ft_max(e,i)*(1 - A(e,i,p,t));
HP_BOILER_LB(e,i,p,t)$(E_FUEL(e) AND UT_B(i) AND PS(p) AND PH(t))..
SUM(ii$ZE(ii,e),FT(e,ii,i,t)) =G= ft_min(e,i,p) +
rhop(e,i,p)*(QB(e,i,t) - qbp_min(e,i,p)) - ft_max(e,i)*(1 - A(e,i,p,t));
SB_RESTART(e,i,t)$(E_FUEL(e) AND UT_B(i) AND PH(t))..
FS(e,i,t) =E= s_fuel(e,i)*S(e,i,t);
HPB_LB_SS(e,i,t)$(E_FUEL(e) AND UT_B(i) AND PH(t))..
QB(e,i,t) =G= SUM(p$PS(p),qbp_min(e,i,p)*A(e,i,p,t));
HPB_UB_SS(e,i,t)$(E_FUEL(e) AND UT_B(i) AND PH(t))..
QB(e,i,t) =L= SUM(p$PS(p),qbp_max(e,i,p)*A(e,i,p,t)) -
q_red(i)*V(i,t);
EMISSIONS(e,i,t)$(E_EMIS(e) AND PH(t) AND UT_B(i))..
QB(e,i,t) =E= SUM((ee,ii)$(E_FUEL(ee) AND
ZE(ii,ee)),coef_emis(ee,e)*(FT(ee,ii,i,t) + FS(ee,i,t)));
R1(i,t)$(PH(t) AND UT_B(i))..
RET(i,t) =E= coef_h(i)*SUM(e$E_FUEL(e),QB(e,i,t));
R2(i,t)$(PH(t) AND UT_B(i))..
BEL(i,t) =E= coef_e(i)*SUM(e$E_FUEL(e),QB(e,i,t));
HP_TURBINE(i,t)$(PH(t) AND UT_T(i))..
HP(i,t) =E= MP(i,t) + LP(i,t) + EP(i,t);
EP_LB(i,t)$(PH(t) AND UT_T(i))..
EP(i,t) =G= ehst(i)*HP(i,t);
HPT_LB(i,t)$(PH(t) AND UT_T(i))..
HP(i,t) =G= hp_min(i)*SUM(e$E_HP(e),X(e,i,t));
HPT_UB(i,t)$(PH(t) AND UT_T(i))..
HP(i,t) =L= hp_max(i)*SUM(e$E_HP(e),X(e,i,t));
EL_TURBINE(i,t)$(PH(t) AND UT_T(i))..
EL(i,t) =E= eff(i)*(HP(i,t)*(hb - hm) + (HP(i,t) - MP(i,t))*(hm - hl) +

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(HP(i,t) - MP(i,t) - LP(i,t))*(hl - he));
MIX_HP(t)$PH(t)..
SUM((e,i)$ (E_FUEL(e) AND UT_B(i)),QB(e,i,t)) - HPM(t) -
SUM(i$UT_T(i),HP(i,t)) =E= SUM(e$E_HP(e),DEM_UT(e,t));
MIX_MP(t)$PH(t)..
HPM(t) + SUM(i$UT_T(i),MP(i,t)) - MPM(t) - SUM(i$UT_B(i),RET(i,t)) =E=
SUM(e$E_MP(e),DEM_UT(e,t));
MIX_LP(t)$PH(t)..
MPM(t) + SUM(i$UT_T(i),LP(i,t)) =E= SUM(e$E_LP(e),DEM_UT(e,t));
DEMAND_EL(t)$PH(t)..
SUM(i$UT_T(i),EL(i,t)) =E= SUM(e$E_EL(e),DEM_UT(e,t)) + SUM(i$UT_B(i),BEL(i,t));
*=====
*===== MULTISTAGE PRODUCTION SYSTEM =====
*=====
EQUATIONS
EQ1,EQ2,EQ3,EQ4,EQ5,EQ7,EQ8_UP,EQ8_LO,EQ10,EQ11_LO,EQ11_UP,EQ12,EQ13,EQ14,EQ15_LO,EQ15_U
P,EQ16,OBJ,EQ17;

EQ1(i,t)$ (PR(i) AND PH(t)).. RP(i,t) =E= RP(i,t-1) - SUM(j$IJ(j,i),XP(j,i,t-tj(j,i))) +
SUM(j$IJ(j,i),XP(j,i,t));
EQ2(i,t)$ (SV(i) AND PH(t)).. RS(i,t) =E= RS(i,t-1) - SUM(e$ZE(i,e),XS(e,i,t-1)) +
SUM(e$ZE(i,e),XS(e,i,t));
EQ3(e,i,t)$ (PR(i) AND J_IN(e,i) AND PH(t))..
SUM(ii$(JC_IN(i,ii) AND J_OUT(e,ii)),FT(e,ii,i,t)) =E=
SUM(j$(EJ_IN(j,e) AND IJ(j,i)), -1*rho(j,e)*B(j,i,t));
EQ4(e,i,t)$ (PR(i) AND J_OUT(e,i) AND PH(t))..
SUM(ii$(JC_OUT(i,ii) AND J_IN(e,ii)),FT(e,i,ii,t)) =E=
SUM(j$(EJ_OUT(j,e) AND IJ(j,i)), rho(j,e)*B(j,i,t-tj(j,i)));
EQ5(e,i,t)$ (SV(i) AND ZE(i,e) AND PH(t))..
BS(e,i,t) =E= BS(e,i,t-1)$ (ORD(t)>1) + s0(e,i)$ (ORD(t)=1) -
SUM(ii$(JC_OUT(i,ii) AND J_IN(e,ii)),FT(e,i,ii,t)) + SUM(ii$(JC_IN(i,ii) AND
J_OUT(e,ii)),FT(e,ii,i,t));
EQ7(e,i,t)$ (PR(i) AND NS(e) AND J_OUT(e,i) AND PH(t))..
SUM(ii$(JC_OUT(i,ii) AND J_IN(e,ii)),WT(e,i,ii,t)) =L= 1;
EQ8_UP(e,i,t)$ (NS(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t-1) =L= SUM(ii$(JC_OUT(i,ii) AND J_IN(e,ii)),FT(e,i,ii,t)) +
smax(ii$(JC_OUT(i,ii) AND J_IN(e,ii)),xi(e,i,ii))*(1- SUM(ii$(JC_OUT(i,ii) AND
J_IN(e,ii)),WT(e,i,ii,t)));
EQ8_LO(e,i,t)$ (NS(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t-1) =G= SUM(ii$(JC_OUT(i,ii) AND J_IN(e,ii)),FT(e,i,ii,t));
EQ10(e,i,t)$ (NM(e) AND PR(i) AND J_IN(e,i) AND PH(t))..
SUM(ii$(JC_IN(i,ii) AND J_OUT(e,ii)),WT(e,ii,i,t)) =L= 1;
EQ11_UP(e,i,t)$ (NM(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t) =L= SUM(ii$(JC_IN(i,ii) AND J_OUT(e,ii)),FT(e,ii,i,t)) +
smax(ii$(JC_IN(i,ii) AND J_OUT(e,ii)),xi(e,ii,i))*(1- SUM(ii$(JC_IN(i,ii) AND
J_OUT(e,ii)),WT(e,ii,i,t)));
EQ11_LO(e,i,t)$ (NM(e) AND ZE(i,e) AND PH(t))..
BS(e,i,t) =G= SUM(ii$(JC_IN(i,ii) AND J_OUT(e,ii)),FT(e,ii,i,t));
EQ12(e,i)$ JC(e,i)..
SUM(t$PH(t), Z(e,i,t)) =E= 1;
EQ13(e,i,t)$ (JC(e,i) AND PH(t))..
thita(e,i)*Z(e,i,t) =E= SUM(ii$(JC_IN(i,ii) AND J_OUT(e,ii)),
FT(e,ii,i,t));
EQ14(e,i,ii,t)$ ((NS(e) OR NM(e)) AND J_OUT(e,i) AND JC_OUT(i,ii) AND J_IN(e,ii) AND
PH(t))..
FT(e,i,ii,t) =L= xi(e,i,ii)*WT(e,i,ii,t);
EQ17(e,i,ii,t)$ ((NS(e) OR NM(e)) AND J_OUT(e,i) AND JC_OUT(i,ii) AND J_IN(e,ii) AND
PH(t))..
FT(e,i,ii,t) =G= (0.2*xi(e,i,ii))*WT(e,i,ii,t);
EQ15_LO(j,i,t)$ (IJ(j,i) AND PH(t)).. B(j,i,t) =G= bitamin(i)*XP(j,i,t);
EQ15_UP(j,i,t)$ (IJ(j,i) AND PH(t)).. B(j,i,t) =L= bitamax(i)*XP(j,i,t);
EQ16(e,i,t)$ (SV(i) AND ZE(i,e) AND PH(t)).. BS(e,i,t) =L= bitamax(i)*XS(e,i,t);
*=====
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*=====
EQUATIONS OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;

OFCL_DM(i,t)$ (UT_B(i) AND IDM(i) AND PH(t) AND (hitap(i,t)>0))..
SUM(e$E_FUEL(e),X(e,i,t)) =E= 0;
OFCL_FM(i)$ (IFM(i))..
SUM((q,t)$ (QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tIs(i))), H(i,q,t)) =E= 1;
OFCL(i,q,t)$ (UT_B(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (UT_B(i) AND IFM(i) AND

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(ORD(t) GE tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1)))..
      SUM(e$E_FUEL(e),X(e,i,t)) + SUM(tt$(PH(tt) AND (ORD(tt) GE
max(tes(i), (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE min(tls(i),ORD(t)))), H(i,q,tt)) =L=
1;
LinkWH(i,t)$PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tls(i)))..
      W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RESOURCE(t)$PH(t)..
* on-line condition-based cleaning
      SUM(i$IOM(i), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
      + SUM((i,q,tt)$PH(tt) AND IOFF_CB(i) AND QI(i,q) AND (ORD(tt) GE
(ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
      + SUM((i,q,tt)$PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE tes(i))
AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
      AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE
min(tls(i),ORD(t))),hres(i,q)*H(i,q,tt))
      =L= hita(t)- SUM(i$IDM(i), hitap(i,t));
=====
*===== DEGRADATION & RECOVERY PERFORMANCE MODEL =====
*=====
EQUATIONS      DEG1,DEG2,DEG3, RECM1,RECM2,RECM2_UB,RECMV,
DQ1,DQ2,DQ2_UB,DQ3,DQ4,DQ5,DQ6,VX,CONOM,VP,PERF;
*DQ2_PR,DQ3_PR,DQV_PR,DQ4_PR,DQ5_PR,DQ6_PR,VE01,VE02,
DEG1(i,t)$PH(t) AND ICBM(i)..
      U(i,t) =L= deg_ub(i)*SUM(e$E_FUEL(e),X(e,i,t));
DEG2(i,t)$PH(t) AND ICBM(i)..
      U(i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) - deg_ub(i)*(1-
SUM(e$E_FUEL(e),X(e,i,t)));
DEG3(i,t)$PH(t) AND ICBM(i)..
      U(i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) + deg_ub(i)*(1-
SUM(e$E_FUEL(e),X(e,i,t)));
RECM1(i,t)$PH(t) AND IOFF_CB(i)..
      R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$PH(t) AND ICBM(i)..
      R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
SUM(e$E_FUEL(e),X(e,i,t))) - bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECMV(i,t)$PH(t) AND IOM(i)..
      R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
1)*(1-recov(i)) - bigM(i,t)*(1-V(i,t));
RECM2_UB(i,t)$PH(t) AND ICBM(i)..
      R(i,t) =L= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
SUM(e$E_FUEL(e),X(e,i,t))) + bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ1(i,t)$PH(t) AND IOFF_CB(i)..
      DQ(i,t) =L= bigM(i,t)*(1-W(i,t));
DQ2(i,t)$PH(t) AND ICBM(i) AND UT(i)..
      DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
DEQ(i,t)) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ3(i,t)$PH(t) AND IOM(i) AND UT_B(i)..
      DQ(i,t) =G= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
DEQ(i,t))*(1-recov(i)) - 1000*(1-V(i,t));
DQ2_UB(i,t)$PH(t) AND ICBM(i) AND UT_B(i)..
      DQ(i,t) =L= (DQ(i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
DEQ(i,t)) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ4(i,t)$PH(t) AND ICBM(i) AND UT_B(i)..
      DEQ(i,t) =L= ((qb_max(i)- SUM(e$E_FUEL(e),QB(e,i,t)))/qb_max(i)) +
1000*(1-SUM(e$E_FUEL(e),X(e,i,t)));
DQ5(i,t)$PH(t) AND ICBM(i) AND UT_B(i)..
      DEQ(i,t) =G= ((qb_max(i)- SUM(e$E_FUEL(e),QB(e,i,t)))/qb_max(i)) -
1000*(1-SUM(e$E_FUEL(e),X(e,i,t)));
DQ6(i,t)$PH(t) AND ICBM(i) AND UT_B(i)..
      DEQ(i,t) =L= 1000*(SUM(e$E_FUEL(e),X(e,i,t)));
VX(i,t)$PH(t) AND IOM(i)..
      V(i,t) =L= SUM(e$E_FUEL(e),X(e,i,t));
CONOM(i,t)$PH(t) AND IOM(i)..
      SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(t)-gap_on(i)+1),t_first)) AND
(ORD(tt) LE ORD(t))), V(i,tt)) =L= 1;
VP(i,t)$PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i)) AND ORD(t) LE (t_first-1+gap_on(i)-
gap_onp(i)).. V(i,t) =E= 0;
PERF(i,t)$ICBM(i) AND PH(t) AND ORD(t)=last_pred_hor)..
      deg_r(i)*R(i,t) + deg_qs(i)*DQ(i,t) =L= 0.75*deg_ub(i);

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*=====linking constraints utility production=====
EQUATIONS      DEMAND_UT,DEM_SEQ;

DEMAND_UT(e,t)$(PH(t) AND E_UT(e)AND PROD_PLAN=0)..
      NS_UT(e,t) + DEM_UT(e,t)=E= SUM((i,j,tt)$(IJ(j,i) AND ORD(tt) GE
(ORD(t)-tj(j,i)+1) AND ORD(tt) LE ORD(t)), alpha(j,i,e)*B(j,i,tt) +
bita(j,i,e)*XP(j,i,tt));

DEM_SEQ(e,t)$(PH(t) AND E_UT(e) AND PROD_PLAN=1)..
      SUM((i,j,tt)$(IJ(j,i) AND ORD(tt) GE (ORD(t)-tj(j,i)+1) AND ORD(tt) LE
ORD(t)), alpha(j,i,e)*B(j,i,tt) + bita(j,i,e)*XP(j,i,tt)) =L= max_avail_e(e,t);
*=====
OBJ(e,i)$JC(e,i)..      OF =G= SUM(t$PH(t),ORD(t)*Z(e,i,t))+ SUM((ee,t)$(PH(t) AND
E_UT(ee)), cost_ns_u(ee,t)*NS_UT(ee,t));

MODEL MULTISTAGE_PROD_UTILITY_SYSTEM /all/;

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## A.3 Chapter 4

### A.3.1 Case Study 1

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*=====
*===== STARTUP and SHUTDOWN =====
*=====
EQUATIONS      SFX1,SFX2,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0;

SFX1(i,t)$(KE(i) AND I_SF(i) AND PH(t))..
      S(i,t) - F(i,t) =E= X(i,t) - xip(i)$(ORD(t)=t_first) - X(i,t-
1)$(ORD(t)>t_first);
SFX2(i,t)$(KE(i) AND I_SF(i) AND PH(t))..
      S(i,t) + F(i,t) =L= 1;
S_MIN(i,t)$(KE(i) AND I_SMIN(i) AND PH(t) AND omega(i)>1)..
      X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omega(i)+1)) AND
ORD(tt) LE ORD(t)),S(i,tt));
S_MIN0(i,t)$(KE(i) AND I_SMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+omega(i)-
omegap(i)) AND (omegap(i)>0 AND omegap(i)<omega(i)))..
      X(i,t) =E= 1;
F_MIN(i,t)$(KE(i) AND I_FMIN(i) AND PH(t) AND psi(i)>1)..
      1 - X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-psi(i)+1))
AND ORD(tt) LE ORD(t)),F(i,tt));
F_MIN0(i,t)$(KE(i) AND I_FMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+psi(i)-psip(i))
AND (psip(i)>0 AND psip(i)<psi(i)))..
      X(i,t) =E= 0;
X_MAX1(i,t)$(KE(i) AND MR(i) AND PH(t))..
      SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omikron(i))) AND ORD(tt) LE
ORD(t)),X(i,tt))
      =L= omikron(i);
X_MAX0(i,t)$(KE(i) AND MR(i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1)) AND
(omegap(i)>1))..
      SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i))))
AND ORD(tt) LE ORD(t)),X(i,tt))
      =L= (omikron(i)-omegap(i));
*=====
*===== PRODUCTION AND UTILITY SYSTEM =====
*=====
EQUATIONS
PROD_LB,PROD_UB,PROD_Y,PROD_YX1,PROD_YX2,UT_QE,UT_LB,UT_UB,Inv_IN,InvIN_LB,InvIN_UB,Inv,
Inv_LB,Inv_UB,InvUT_OUT,InvUT_LB,InvUT_UB,DEM_FP,DEM_UT;

PROD_LB(n,i,e,t)$(N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
      QE(n,i,e,t) =G= qe_min(i,e,t)*Y(i,e,t);
PROD_UB(n,i,e,t)$(N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
      QE(n,i,e,t) =L= qe_max(i,e,t)*(Y(i,e,t) - (q_red(i)*VE(i,e,t))$IOM(i));
PROD_Y(i,t)$(KE(i) AND PH(t) AND PR(i))..
      SUM(e$EI(i,e),Y(i,e,t)) =L= 1;
PROD_YX1(i,e,t)$(KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
      Y(i,e,t) =L= X(i,t);
PROD_YX2(i,t)$(KE(i) AND PH(t) AND PR(i))..
      X(i,t) =L= SUM(e$EI(i,e),Y(i,e,t));

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UT_QE(n,i,e,t)$(N_SP(n) AND KE(i) AND PH(t) AND UT(i) AND EI(i,e))..
    QE(n,i,e,t) =E= coef_e(i,e)*QS(n,i,t);
UT_LB(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND UT(i))..
    QS(n,i,t) =G= qs_min(i,t)*X(i,t);
UT_UB(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND UT(i))..
    QS(n,i,t) =L= qs_max(i,t)*(X(i,t) - (q_red(i)*V(i,t))$IOM(i));
Inv_IN(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B_IN(n,e,z,t) =E= SUM(i$(KE(i) AND EI(i,e) AND
ZI_IN(z,i)),QE(n,i,e,t));
InvIN_LB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(n,e,z,t) =G= bin_min(e,z,t);
InvIN_UB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(n,e,z,t) =L= bin_max(e,z,t);
Inv(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B(n,e,z,t) =E= bitap(e,z)$(ORD(t)=t_first) + (1-bitaz(z))*B(n,e,z,t-
1)$(ORD(t)>t_first) + B_IN(n,e,z,t) - B_OUT(n,e,z,t);
Inv_LB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B(n,e,z,t) =G= b_min(e,z);
Inv_UB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B(n,e,z,t) =L= b_max(e,z);
InvUT_OUT(n,e,z,t)$(N_SP(n) AND PH(t) AND E_UT(e) AND ZE(z,e))..
    B_OUT(n,e,z,t) =E= SUM(i$(KE(i) AND PR(i) AND ZI_OUT(z,i)),
BU_OUT(n,e,z,i,t));
InvUT_LB(n,e,z,t)$(N_SP(n) AND PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(n,e,z,t) =G= bout_min(e,z,t);
InvUT_UB(n,e,z,t)$(N_SP(n) AND PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(n,e,z,t) =L= bout_max(e,z,t);
DEM_FP(n,e,t)$(N_SP(n) AND PH(t) AND E_PR(e))..
    SUM(z$ZE(z,e), B_OUT(n,e,z,t)) + NS_PR(n,e,t) =E= thita_n(n,e,t);
DEM_UT(n,e,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND E_UT(e) AND IE_PR(i,e))..
    NS_UT(n,e,i,t) + SUM(z$(ZE(z,e) AND ZI_OUT(z,i)), BU_OUT(n,e,z,i,t))
    =E= SUM(ee$(E_PR(ee) AND EI(i,ee)), alpha(i,ee,e)*QE(n,i,ee,t) +
bita(i,ee,e)*Y(i,ee,t));
*=====
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*=====
EQUATIONS    OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;

OFCL_DM(i,t)$(KE(i) AND PH(t) AND IDM(i,t))..
    X(i,t) =E= 0;
OFCL_FM(i,t)$(KE(i) AND IFM(i))..
    SUM((q,t)$(QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tls(i))), H(i,q,t)) =E= 1;
OFCL(i,q,t)$(KE(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))))..
    X(i,t) + SUM(tt$(PH(tt) AND (ORD(tt) GE max(tes(i), (ORD(t)-
ni_q(i,q)+1))) AND (ORD(tt) LE min(tls(i),ORD(t))))) , H(i,q,tt)) =L= 1;
LinkWH(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE tls(i))))..
    W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RSOURCE(t)$(PH(t))..
* on-line condition-based cleaning
    SUM(i$(KE(i) AND IOM(i)), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND
(ORD(tt) GE (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i),ORD(t))))) ,hres(i,q)*H(i,q,tt))
    =L= hita(t) - SUM(i$(KE(i) AND IDM(i,t)), hitap(i,t));
*=====
*===== DEGRADATION & RECOVERY PERFORMANCE MODEL =====
*=====
EQUATIONS    DEG1,DEG2,DEG3, RECM1,RECM2,RECM2_UB,RECMV,
DQ1,DQ2,DQ2_UB,DQ3,DQ4,DQ5,DQ6, DQ2_PR,DQ3_PR,DQV_PR, VX,CONOM,VP, VE01,VE02, PERF;

DEG1(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND ICBM(i))..
    U(n,i,t) =L= deg_ub(i)*X(i,t);
DEG2(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND ICBM(i))..
    U(n,i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*DQ(n,i,t) - deg_ub(i)*(1-
X(i,t));

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DEG3(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i))..
    U(n,i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*DQ(n,i,t) + deg_ub(i)*(1-
X(i,t));
RECM1(i,t)$ (KE(i) AND PH(t) AND IOFF_CB(i))..
    R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
    R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t)) - bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECMV(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
    R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
1)*(1-recov(i)) - bigM(i,t)*(1-V(i,t));
RECM2_UB(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
    R(i,t) =L= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t)) + bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ1(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IOFF_CB(i))..
    DQ(n,i,t) =L= bigM(i,t)*(1-W(i,t));
DQ2(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
DEQ(n,i,t)) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ3(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IOM(i) AND UT(i))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
DEQ(n,i,t))*(1-recov(i)) - 1000*(1-V(i,t));
DQ2_UB(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DQ(n,i,t) =L= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
DEQ(n,i,t)) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ2_PR(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(n,i,e,t))/qe_max(i,e,t)) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i))
- deg_ub(i)*(1-Y(i,e,t)));
DQ3_PR(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
    DQ(n,i,t) =L= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(n,i,e,t))/qe_max(i,e,t)) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i))
+ deg_ub(i)*(1-Y(i,e,t)));
DQV_PR(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(i)$ (ORD(t)=t_first) +
((qe_max(i,e,t)-QE(n,i,e,t))/qe_max(i,e,t))*(1-recov(i)) - 1000*(1-V(i,t)) -
deg_ub(i)*(1-Y(i,e,t)));
DQ4(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DEQ(n,i,t) =L= ((qs_max(i,t)-QS(n,i,t))/qs_max(i,t)) + 1000*(1-X(i,t));
DQ5(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DEQ(n,i,t) =G= ((qs_max(i,t)-QS(n,i,t))/qs_max(i,t)) - 1000*(1-X(i,t));
DQ6(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DEQ(n,i,t) =L= 1000*(X(i,t));
VX(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
    V(i,t) =L= X(i,t);
CONOM(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
    SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(tt)-gap_on(i)+1),t_first)) AND
(ORD(tt) LE ORD(tt))), V(i,tt)) =L= 1;
VP(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i)) AND ORD(t) LE (t_first-
1+gap_on(i)-gap_onp(i)))..
    V(i,t) =E= 0;
VE01(i,e,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
    VE(i,e,t) =L= Y(i,e,t);
VE02(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i))..
    V(i,t) =E= SUM(e$EI(i,e),VE(i,e,t));
PERF(n,i,t)$ (N_SP(n) AND KE(i) AND ICBM(i) AND PH(t) AND ORD(t)=14)..
    deg_r(i)*R(i,t) + deg_qs(i)*DQ(n,i,t) =L= 0.75*deg_ub(i);

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EQUATION OBJECTIVE;

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OBJECTIVE..      OF =E=
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*=====  

1st Stage Variables
*=====  

    SUM((i,t)$ (KE(i) AND I_SF(i) AND PH(t)),  

((cost_s(i,t)*S(i,t)+(cost_f(i,t)*F(i,t))))  

    + SUM((i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e)),  

cost_y(i,e,t)*Y(i,e,t))  

    + SUM((i,t)$ (KE(i) AND PH(t) AND UT(i)), cost_x(i,t)*X(i,t))  

    + SUM((i,q,t)$ (KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),  

cost_h(i,q,t)*H(i,q,t))  

    + SUM((i,t)$ (KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*V(i,t))
*=====  

2nd Stage Variables
*=====

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+ SUM((n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
prob(n)*cost_qe(i,e,t)*QE(n,i,e,t)
+ SUM((n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND UT(i)),
prob(n)*cost_qs(i,t)*QS(n,i,t)
+ SUM((n,e,t)$ (N_SP(n) AND E_PR(e) AND PH(t)),
prob(n)*cost_ns_p(e,t)*NS_PR(n,e,t)
+ SUM((n,e,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IE_PR(i,e)),
prob(n)*cost_ns_u(e,i,t)*NS_UT(n,e,i,t)
+ SUM((n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i)),
prob(n)*cost_u(i,t)*U(n,i,t));
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MODEL UTILITY\_PROD\_SYSTEM\_RH\_STOCH /ALL/;

## A.3.2 Case Study 2

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=====
*----- STARTUP and SHUTDOWN -----
=====
EQUATIONS
SFX1,SFX2,S_MIN,F_MIN,S_MIN0,F_MIN0,X_MAX1,X_MAX0;

SFX1(i,t)$ (KE(i) AND I_SF(i) AND PH(t))..
S(i,t) - F(i,t) =E= X(i,t) - xip(i)$ (ORD(t)=t_first) - X(i,t-
1)$ (ORD(t)>t_first);
SFX2(i,t)$ (KE(i) AND I_SF(i) AND PH(t))..
S(i,t) + F(i,t) =L= 1;
S_MIN(i,t)$ (KE(i) AND I_SMIN(i) AND PH(t) AND omega(i)>1)..
X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omega(i)+1)) AND
ORD(tt) LE ORD(t)),S(i,tt));
S_MIN0(i,t)$ (KE(i) AND I_SMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+omega(i)-
omegap(i))) AND (omegap(i)>0 AND omegap(i)<omega(i)))..
X(i,t) =E= 1;
F_MIN(i,t)$ (KE(i) AND I_FMIN(i) AND PH(t) AND psi(i)>1)..
1 - X(i,t) =G= SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-psi(i)+1))
AND ORD(tt) LE ORD(t)),F(i,tt));
F_MIN0(i,t)$ (KE(i) AND I_FMIN(i) AND PH(t) AND (ORD(t) LE (t_first-1+psi(i)-psip(i))
AND (psip(i)>0 AND psip(i)<psi(i)))..
X(i,t) =E= 0;
X_MAX1(i,t)$ (KE(i) AND MR(i) AND PH(t))..
SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-omikron(i))) AND ORD(tt) LE
ORD(t)),X(i,tt))
=L= omikron(i);
X_MAX0(i,t)$ (KE(i) AND MR(i) AND PH(t) AND (ORD(t)=(omikron(i)-omegap(i)+1)) AND
(omegap(i)>1))..
SUM(tt$(PH(tt) AND ORD(tt) GE max(1,(ORD(t)-(omikron(i)-omegap(i))))
AND ORD(tt) LE ORD(t)),X(i,tt))
=L= (omikron(i)-omegap(i));
=====
*----- PRODUCTION AND UTILITY SYSTEM -----
=====
EQUATIONS
PROD_LB,PROD_UB,PROD_Y,PROD_YX1,PROD_YX2,UT_QE,UT_LB,UT_UB,Inv_IN,InvIN_LB,InvIN_UB,Inv,
Inv_LB,Inv_UB,InvUT_OUT,InvUT_LB,InvUT_UB,DEM_FP,DEM_UT;

PROD_LB(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
QE(n,i,e,t) =G= qe_min(i,e,t)*Y(i,e,t);
PROD_UB(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
QE(n,i,e,t) =L= qe_max(i,e,t)*(Y(i,e,t) - (q_red(i)*VE(i,e,t))$IOM(i));
PROD_Y(i,t)$ (KE(i) AND PH(t) AND PR(i))..
SUM(e$EI(i,e),Y(i,e,t)) =L= 1;
PROD_YX1(i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e))..
Y(i,e,t) =L= X(i,t);
PROD_YX2(i,t)$ (KE(i) AND PH(t) AND PR(i))..
X(i,t) =L= SUM(e$EI(i,e),Y(i,e,t));
UT_QE(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND UT(i) AND EI(i,e))..
QE(n,i,e,t) =E= coef_e(i,e)*QS(n,i,t);
UT_LB(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND UT(i))..
QS(n,i,t) =G= qs_min(i,t)*X(i,t);
UT_UB(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND UT(i))..
QS(n,i,t) =L= qs_max(i,t)*(X(i,t) - (q_red(i)*V(i,t))$IOM(i));
Inv_IN(n,e,z,t)$ (N_SP(n) AND PH(t) AND ZE(z,e))..
B_IN(n,e,z,t) =E= SUM(i$(KE(i) AND EI(i,e) AND

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ZI_IN(z,i),QE(n,i,e,t));
InvIN_LB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(n,e,z,t) =G= bin_min(e,z,t);
InvIN_UB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e) AND bin_cons=1)..
    B_IN(n,e,z,t) =L= bin_max(e,z,t);
Inv(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B(n,e,z,t) =E= bitap(n,e,z)$(ORD(t)=t_first) + (1-bitaz(z))*B(n,e,z,t-
1)$(ORD(t)>t_first) + B_IN(n,e,z,t) - B_OUT(n,e,z,t);
Inv_LB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B(n,e,z,t) =G= b_min(e,z);
Inv_UB(n,e,z,t)$(N_SP(n) AND PH(t) AND ZE(z,e))..
    B(n,e,z,t) =L= b_max(e,z);
InvUT_OUT(n,e,z,t)$(N_SP(n) AND PH(t) AND E_UT(e) AND ZE(z,e))..
    B_OUT(n,e,z,t) =E= SUM(i$(KE(i) AND PR(i) AND ZI_OUT(z,i)),
BU_OUT(n,e,z,i,t));
InvUT_LB(n,e,z,t)$(N_SP(n) AND PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(n,e,z,t) =G= bout_min(e,z,t);
InvUT_UB(n,e,z,t)$(N_SP(n) AND PH(t) AND E_UT(e) AND ZE(z,e) AND bout_cons=1)..
    B_OUT(n,e,z,t) =L= bout_max(e,z,t);
DEM_FP(n,e,t)$(N_SP(n) AND PH(t) AND E_PR(e))..
    SUM(z$ZE(z,e), B_OUT(n,e,z,t)) + NS_PR(n,e,t) =E= thita_n(n,e,t);
DEM_UT(n,e,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND E_UT(e) AND IE_PR(i,e))..
    NS_UT(n,e,i,t) + SUM(z$(ZE(z,e) AND ZI_OUT(z,i)), BU_OUT(n,e,z,i,t))
    =E= SUM(ee$(E_PR(ee) AND EI(i,ee)), alpha(i,ee,e)*QE(n,i,ee,t) +
bita(i,ee,e)*Y(i,ee,t));
*=====
*===== CLEANING PLANNING FOR UTILITY & PRODUCTION SYSTEM =====
*=====
EQUATIONS    OFCL_DM,OFCL_FM,OFCL,LinkWH,CL_RSOURCE;

OFCL_DM(i,t)$(KE(i) AND PH(t) AND IDM(i,t))..
    X(i,t) =E= 0;
OFCL_FM(i,t)$(KE(i) AND IFM(i))..
    SUM((q,t)$(QI(i,q) AND PH(t) AND (ORD(t) GE tes(i)) AND (ORD(t) LE
tls(i))), H(i,q,t)) =E= 1;
OFCL(i,q,t)$(KE(i) AND QI(i,q) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))))..
    X(i,t) + SUM(tt$(PH(tt) AND (ORD(tt) GE max(tes(i), (ORD(t)-
ni_q(i,q)+1))) AND (ORD(tt) LE min(tls(i),ORD(t)))), H(i,q,tt)) =L= 1;

LinkWH(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i) OR (IFM(i) AND (ORD(t) GE tes(i)) AND
(ORD(t) LE tls(i))))..
    W(i,t) =E= SUM(q$QI(i,q),H(i,q,t));
CL_RSOURCE(t)$PH(t)..
* on-line condition-based cleaning
    SUM(i$(KE(i) AND IOM(i)), hresV_onWash(i)*V(i,t))
* off-line condition-based cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND
(ORD(tt) GE (ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))),hres(i,q)*H(i,q,tt))
* off-line flexible time-window cleaning
    + SUM((i,q,tt)$(KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE
tes(i)) AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i),ORD(t))),hres(i,q)*H(i,q,tt))
    =L= hita(t) - SUM(i$(KE(i) AND IDM(i,t)), hitap(i,t));
*=====
*===== DEGRADATION & RECOVERY PERFORMANCE MODEL =====
*=====
EQUATIONS    DEG1,DEG2,DEG3, RECM1,RECM2,RECM2_UB,RECMV,
DQ1,DQ2,DQ2_UB,DQ3,DQ4,DQ5,DQ6, DQ2_PR,DQ3_PR,DQV_PR,DQ4_PR,DQ5_PR,DQ6_PR, VX,CONOM,VP,
VE01,VE02,PERF;
DEG1(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND ICBM(i))..
    U(n,i,t) =L= deg_ub(i)*X(i,t);
DEG2(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND ICBM(i))..
    U(n,i,t) =G= deg_r(i)*R(i,t) + deg_qs(i)*DQ(n,i,t) - deg_ub(i)*(1-
X(i,t));
DEG3(n,i,t)$(N_SP(n) AND KE(i) AND PH(t) AND ICBM(i))..
    U(n,i,t) =L= deg_r(i)*R(i,t) + deg_qs(i)*DQ(n,i,t) + deg_ub(i)*(1-
X(i,t));
RECM1(i,t)$(KE(i) AND PH(t) AND IOFF_CB(i))..
    R(i,t) =L= bigM(i,t)*(1-W(i,t));
RECM2(i,t)$(KE(i) AND PH(t) AND ICBM(i))..
    R(i,t) =G= (R(i,t-1)$(ORD(t)>t_first) + dsp(i)$(ORD(t)=t_first) +

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X(i,t) - bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
RECMV(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
    R(i,t) =G= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
1)*(1-recov(i)) - bigM(i,t)*(1-V(i,t));
RECM2_UB(i,t)$ (KE(i) AND PH(t) AND ICBM(i))..
    R(i,t) =L= (R(i,t-1)$ (ORD(t)>t_first) + dsp(i)$ (ORD(t)=t_first) +
X(i,t) + bigM(i,t)*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ1(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IOFF_CB(i))..
    DQ(n,i,t) =L= bigM(i,t)*(1-W(i,t));
DQ2(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(n,i)$ (ORD(t)=t_first)
+ DEQ(n,i,t) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ3(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IOM(i) AND UT(i))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(n,i)$ (ORD(t)=t_first)
+ DEQ(n,i,t))*(1-recov(i)) - 1000*(1-V(i,t));
DQ2_UB(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DQ(n,i,t) =L= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(n,i)$ (ORD(t)=t_first)
+ DEQ(n,i,t) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ2_PR(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(n,i)$ (ORD(t)=t_first)
+ SUM(e$EI(i,e),DEQ_E(n,i,e,t))) - 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQ3_PR(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i))..
    DQ(n,i,t) =L= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(n,i)$ (ORD(t)=t_first)
+ SUM(e$EI(i,e),DEQ_E(n,i,e,t))) + 1000*(W(i,t)$IOFF_CB(i) + V(i,t)$IOM(i));
DQV_PR(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IOM(i) AND PR(i))..
    DQ(n,i,t) =G= (DQ(n,i,t-1)$ (ORD(t)>t_first) + dqp(n,i)$ (ORD(t)=t_first)
+ SUM(e$EI(i,e),DEQ_E(n,i,e,t)))*(1-recov(i)) - 1000*(1-V(i,t));
DQ4(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DEQ(n,i,t) =L= ((qs_max(i,t)-QS(n,i,t))/qs_max(i,t) + 1000*(1-X(i,t)));
DQ5(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DEQ(n,i,t) =G= ((qs_max(i,t)-QS(n,i,t))/qs_max(i,t) - 1000*(1-X(i,t)));
DQ6(n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND UT(i))..
    DEQ(n,i,t) =L= 1000*(X(i,t));

DQ4_PR(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
    DEQ_E(n,i,e,t) =L= ((qe_max(i,e,t)-QE(n,i,e,t))/qe_max(i,e,t)) +
deg_ub(i)*(1-Y(i,e,t));
DQ5_PR(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
    DEQ_E(n,i,e,t) =G= ((qe_max(i,e,t)-QE(n,i,e,t))/qe_max(i,e,t)) -
deg_ub(i)*(1-Y(i,e,t));
DQ6_PR(n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i) AND PR(i) AND EI(i,e))..
    DEQ_E(n,i,e,t) =L= 1000*Y(i,e,t);
VX(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
    V(i,t) =L= X(i,t);
CONOM(i,t)$ (KE(i) AND PH(t) AND IOM(i))..
    SUM(tt$(PH(tt) AND (ORD(tt) GE max((ORD(t)-gap_on(i)+1),t_first)) AND
(ORD(tt) LE ORD(tt)), V(i,tt)) =L= 1;
VP(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND (gap_onp(i)<gap_on(i) AND ORD(t) LE (t_first-
1+gap_on(i)-gap_onp(i))))..
    V(i,t) =E= 0;
VE01(i,e,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i) AND EI(i,e))..
    VE(i,e,t) =L= Y(i,e,t);
VE02(i,t)$ (KE(i) AND PH(t) AND IOM(i) AND PR(i))..
    V(i,t) =E= SUM(e$EI(i,e),VE(i,e,t));
*for the last time period t
PERF(n,i,t)$ (N_SP(n) AND KE(i) AND ICBM(i) AND PH(t) AND ORD(t)=last_pred_hor)..
deg_r(i)*R(i,t) + deg_qs(i)*DQ(n,i,t) =L= 0.75*deg_ub(i);
*=====
*=====
EQUATION OBJECTIVE;

OBJECTIVE..      OF =E=
*===== 1st Stage Variables =====
    SUM((i,t)$ (KE(i) AND I_SF(i) AND PH(t)),
((cost_s(i,t)*S(i,t)+(cost_f(i,t)*F(i,t))))
+ SUM((i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
cost_y(i,e,t)*Y(i,e,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND UT(i)), cost_x(i,t)*X(i,t))
+ SUM((i,q,t)$ (KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),
cost_h(i,q,t)*H(i,q,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*V(i,t))
*===== 2nd Stage Variables =====

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+ SUM((n,i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
prob(n)*cost_qe(i,e,t)*QE(n,i,e,t))
+ SUM((n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND UT(i)),
prob(n)*cost_qs(i,t)*QS(n,i,t))
+ SUM((n,e,t)$ (N_SP(n) AND E_PR(e) AND PH(t)),
prob(n)*cost_ns_p(e,t)*NS_PR(n,e,t))
+ SUM((n,e,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IE_PR(i,e)),
prob(n)*cost_ns_u(e,i,t)*NS_UT(n,e,i,t))
+ SUM((n,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i)),
prob(n)*cost_u(i,t)*U(n,i,t));
*=====
MODEL UTILITY_PROD_SYSTEM_RH_STOCH /ALL/;
*=====
*=====
*=====
SET      iter      /it1*it28/;

PARAMETERS
save_B(iter,n,e,z,t), save_X(iter,i,t), save_Y(iter,i,e,t), save_S(iter,i,t),
save_F(iter,i,t), save_W(iter,i,t), save_H(iter,i,q,t),
save_V(iter,i,t), save_VE(iter,i,e,t), save_B_OUT(iter,n,e,z,t), save_B_IN(iter,n,e,z,t),
save_BU_OUT(iter,n,e,z,i,t), save_NS_UT(iter,n,e,i,t), save_NS_PR(iter,n,e,t),
save_QS(iter,n,i,t), save_QE(iter,n,i,e,t), save_R(iter,i,t), save_DQ(iter,n,i,t), save_U(it
er,n,i,t), save_DEQ(iter,n,i,t), save_DEQ_E(iter,n,i,e,t),
save_hres(iter,i,t), max_tres(i), counter, step, max_iter, pred_hor, control_hor,
total_hor, thita_it(iter,n,e,t), model_stat(iter), CPUs(iter), active_n(iter);
max_tres(i) = smax(q$(KE(i) AND QI(i,q)), ni_q(i,q));
total_hor      = 28;
pred_hor       = 7;
control_hor    = 1;
step           = control_hor;
max_iter       = total_hor;

save_B(iter,n,e,z,t)=0; save_X(iter,i,t)=0; save_R(iter,i,t)=0; save_V(iter,i,t)=0;
save_hres(iter,i,t)=0; save_DQ(iter,n,i,t)=0;
thita_it(iter,n,e,t) = thita_n(n,e,t);

DISPLAY max_tres, step,max_iter, pred_hor,control_hor,total_hor;

*$ONTEXT
*=====
last_pred_hor = 0;
PH(t) = NO;
active_n(iter) = uniformint(1,3);
DISPLAY active_n;
FOR(counter=1 to max_iter by step,

*===== UPDATE OF PARAMETERS =====
PH(t)$ (ORD(t) GE counter AND ORD(t) LE (counter + pred_hor - 1)) = YES;
t_first = counter;

IF(counter>1,
bitap(n,e,z)      = SUM((iter,t,nn)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-1)
AND ORD(nn)=active_n(iter)), save_B(iter,nn,e,z,t) );
xip(i)$KE(i)      = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-1)),
save_X(iter,i,t) );
dsp(i)$ (KE(i) AND ICBM(i)) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND
ORD(t)=(counter-1)), save_R(iter,i,t) );
dqp(n,i)$ (KE(i) AND ICBM(i)) = SUM((iter,t,nn)$ (ORD(iter)=(counter-1) AND
ORD(t)=(counter-1) AND ORD(nn)=active_n(iter)), save_DQ(iter,nn,i,t) );
omegap(i)$KE(i)   = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (omegap(i)*save_X(iter,i,t) + save_X(iter,i,t)) );
psip(i)$KE(i)     = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (psip(i)*(1-save_X(iter,i,t)) + (1-save_X(iter,i,t))) );
gap_onp(i)$IOM(i) = SUM((iter,t)$ (ORD(iter)=(counter-1) AND ORD(t)=(counter-
1)), (gap_onp(i)*(1-save_V(iter,i,t)) + (1-save_V(iter,i,t))) );
hitap(i,t)$ (KE(i) AND ORD(t) GE counter AND ORD(t) LE (counter+max_tres(i)-1)) =
SUM(iter$(ORD(iter)=(counter-1) AND (SUM(tt$(ORD(tt)=t_first-
1), save_hres(iter,i,tt)>0)), save_hres(iter,i,t) );
IDM(i,t)$ (KE(i) AND ORD(t) GE counter AND hitap(i,t)>0) = YES;
);
last_pred_hor = (pred_hor-control_hor+counter);

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DISPLAY last_pred_hor;

B.lo(n,e,z,t)$ (ORD(t)=(pred_hor-control_hor+counter)) = 0.10*b_max(e,z);

SOLVE UTILITY_PROD_SYSTEM_RH_STOCH using MIP minimizing OF;
      model_stat(iter)$ (ORD(iter)=counter) =
UTILITY_PROD_SYSTEM_RH_STOCH.modelstat;
      CPUs(iter)$ (ORD(iter)=counter) = UTILITY_PROD_SYSTEM_RH_STOCH.resusd;
*===== SAVE SOLUTION FOR THE CH OF THE CURRENT PH =====
save_B(iter,n,e,z,t) $ (ORD(iter)=counter AND ORD(t)=counter) = B.l(n,e,z,t);
save_X(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = X.l(i,t);
save_Y(iter,i,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = Y.l(i,e,t);
save_S(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = S.l(i,t);
save_F(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = F.l(i,t);
save_W(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = W.l(i,t);
save_H(iter,i,q,t) $ (ORD(iter)=counter AND ORD(t)=counter) = H.l(i,q,t);
save_V(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = V.l(i,t);
save_VE(iter,i,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = VE.l(i,e,t);
save_B_OUT(iter,n,e,z,t) $ (ORD(iter)=counter AND ORD(t)=counter) = B_OUT.l(n,e,z,t);
save_B_IN(iter,n,e,z,t) $ (ORD(iter)=counter AND ORD(t)=counter) = B_IN.l(n,e,z,t);
save_BU_OUT(iter,n,e,z,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) =
BU_OUT.l(n,e,z,i,t);
save_NS_UT(iter,n,e,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = NS_UT.l(n,e,i,t);
save_NS_PR(iter,n,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = NS_PR.l(n,e,t);
save_QS(iter,n,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = QS.l(n,i,t);
save_QE(iter,n,i,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = QE.l(n,i,e,t);
save_R(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = R.l(i,t);
save_DQ(iter,n,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = DQ.l(n,i,t);
save_U(iter,n,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = U.l(n,i,t);
save_DEQ(iter,n,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = DEQ.l(n,i,t);
save_DEQ_E(iter,n,i,e,t) $ (ORD(iter)=counter AND ORD(t)=counter) = DEQ_E.l(n,i,e,t);
save_hres(iter,i,t) $ (ORD(iter)=counter AND ORD(t)=counter) = hitap(i,t)
+ SUM((q,tt)$ (KE(i) AND PH(tt) AND IOFF_CB(i) AND QI(i,q) AND (ORD(tt) GE
(ORD(t)-ni_q(i,q)+1)) AND (ORD(tt) LE ORD(t))), hres(i,q)*H.l(i,q,tt))
+ SUM((q,tt)$ (KE(i) AND PH(tt) AND IFM(i) AND QI(i,q) AND (ORD(t) GE tes(i)
AND (ORD(t) LE (tls(i)+ni_q(i,q)-1))
AND (ORD(tt) GE max(tes(i), (ORD(t)-ni_q(i,q)+1))) AND (ORD(tt) LE
min(tls(i), ORD(t))))), hres(i,q)*H.l(i,q,tt));
*=====
DISPLAY counter, PH, hitap, xip, dsp, dqp, omegap, psip, gap_onp, hitap, IDM, thita, save_B, save_X,
save_Y, save_S, save_F, save_W, save_H, save_V, save_VE, save_B_OUT, save_B_IN, save_BU_OUT, save_
NS_UT, save_NS_PR, save_QS, save_QE, save_R, save_DQ, save_U, save_DEQ, save_DEQ_E, save_hres,
thita_it;

DISPLAY
model_stat, CPUs, OF.L, B_IN.L, B_OUT.L, B.L, BU_OUT.L, QS.L, QE.L, NS_UT.L, NS_PR.L, U.l, R.l, DQ.l,
DEQ.l, DEQ_E.l, X.L, S.L, F.L, V.l, VE.l, W.L, H.L, Y.L, KE, ICBM, IFM, IOM, IOFF_CB;

OPTION Clear=PH, Clear=hitap, Clear=IDM, Clear=B_IN, Clear=B_OUT, Clear=B,
Clear=BU_OUT, Clear=QS, Clear=QE, Clear=NS_UT, Clear=NS_PR, Clear=U, Clear=R, Clear=DQ,
Clear=DEQ, Clear=DEQ_E, Clear=X, Clear=S, Clear=F, Clear=V, Clear=H, Clear=VE, Clear=W,
Clear=Y;
);
PH(t)$ (ORD(t) LE counter) = YES;
PARAMETERS OBJ_RH(iter), OBJ_RH_TOTAL;

OBJ_RH(iter) =
*===== 1st Stage Variables =====
      SUM((i,t)$ (KE(i) AND I_SF(i) AND PH(t)),
((cost_s(i,t)*save_S(iter,i,t)+(cost_f(i,t)*save_F(iter,i,t))))
+ SUM((i,e,t)$ (KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
cost_y(i,e,t)*save_Y(iter,i,e,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND UT(i)), cost_x(i,t)*save_X(iter,i,t))
+ SUM((i,q,t)$ (KE(i) AND PH(t) AND (IFM(i) OR IOFF_CB(i)) AND QI(i,q)),
cost_h(i,q,t)*save_H(iter,i,q,t))
+ SUM((i,t)$ (KE(i) AND PH(t) AND IOM(i)), cost_v(i,t)*save_V(iter,i,t))
*===== 2nd Stage Variables =====
+ SUM(n$ (ORD(n)=active_n(iter)),
SUM((i,e,t)$ (N_SP(n) AND KE(i) AND PH(t) AND PR(i) AND EI(i,e)),
prob(n)*cost_qe(i,e,t)*save_QE(iter,n,i,e,t))
+ SUM((i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND UT(i)),
prob(n)*cost_qs(i,t)*save_QS(iter,n,i,t))
+ SUM((e,t)$ (N_SP(n) AND E_PR(e) AND PH(t)),

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prob(n)*cost_ns_p(e,t)*save_NS_PR(iter,n,e,t)
+ SUM((e,i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND IE_PR(i,e)),
prob(n)*cost_ns_u(e,i,t)*save_NS_UT(iter,n,e,i,t)
+ SUM((i,t)$ (N_SP(n) AND KE(i) AND PH(t) AND ICBM(i)),
prob(n)*cost_u(i,t)*save_U(iter,n,i,t));
OBJ_RH_TOTAL = SUM(iter, OBJ_RH(iter));

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## A.4 Chapter 5

### A.4.1 Equations Coding

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EQUATIONS EQ1,EQ2a,EQ2b, EQB1,EQB2a,EQB2b, EQt1,EQ2ta,EQ2tb,
EQ3pa,EQ3pb,EQ3ta,EQ3tb,EQ4a,EQ4b, EQ5,EQ6,EQ7, EQ8,EQ9,EQ10,EQ11,EQ11t,EQ11B,EQ12,
EQ13,EQ14,EQ15,EQ15b, EQ16,EQ17,EQ18,EQ19,EQ20, EQ21,EQ8B,EQ9B,EQ10B;
*===== D E S I G N =====
EQ1(z,j,t) $(TIP_t(t) AND Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j)))..
F(z,j,t) =e= F(z,j,t-1)$ (ord(t)>1) + f0(z,j)$ (ord(t)=1) + E(z,j,t);
EQ2a(z,j,t)$(TIP_t(t) AND Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j)))..
E(z,j,t) =g= gamma_min(z,j,t)*Y(z,j,t-mu(z,j,t));
EQ2b(z,j,t)$(TIP_t(t) AND Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j)))..
E(z,j,t) =l= gamma_max(z,j,t)*Y(z,j,t-mu(z,j,t));

EQB1(z,s,j,t) $(TIP_t(t) AND Z_in(z) and JZ(j,z) and SZ(s,z) and J_B(j) AND JS(j,s) AND
S_B_lim(s))..
FB(z,s,j,t) =e= FB(z,s,j,t-1)$ (ord(t)>1) + fb0(z,s,j)$ (ord(t)=1) + EB(z,s,j,t);
EQB2a(z,s,j,t)$(TIP_t(t) AND Z_in(z) and JZ(j,z) and SZ(s,z) and J_B(j) AND JS(j,s) AND
S_B_lim(s))..
EB(z,s,j,t) =g= gamma_min(z,j,t)*YB(z,s,j,t-mu(z,j,t));
EQB2b(z,s,j,t)$(TIP_t(t) AND Z_in(z) and JZ(j,z) and SZ(s,z) and J_B(j) AND JS(j,s) AND
S_B_lim(s))..
EB(z,s,j,t) =l= gamma_max(z,j,t)*YB(z,s,j,t-mu(z,j,t));
EQt1(z,zz,j,t) $(TIP_t(t) AND Z_in(z) and JZ(j,z) and JZ(j,zz) and J_T(j) and
ZZ_t(z,zz))..
FT(z,zz,j,t) =e= FT(z,zz,j,t-1)$ (ord(t)>1) + ff0(z,zz,j)$ (ord(t)=1) +
ET(z,zz,j,t);
EQ2ta(z,zz,j,t)$(TIP_t(t) AND Z_in(z) and JZ(j,z) and JZ(j,zz) and J_T(j) and
ZZ_t(z,zz))..
ET(z,zz,j,t) =g= gamma_min(z,j,t)*YT(z,zz,j,t-mu_t(z,zz,j,t));
EQ2tb(z,zz,j,t)$(TIP_t(t) AND Z_in(z) and JZ(j,z) and JZ(j,zz) and J_T(j) and
ZZ_t(z,zz))..
ET(z,zz,j,t) =l= gamma_max(z,j,t)*YT(z,zz,j,t-mu_t(z,zz,j,t));
*===== L I N K D E S I G N - P L A N N I N G =====
EQ3pa(z,i,j,t)$(TIP_t(t) AND (J_C(j) OR J_E(j)) and Z_in(z) and JI(j,i) and JZ(j,z))..
P(z,z,i,j,t) =g= alpha_min(z,z,i,j,t)*F(z,j,t);
EQ3pb(z,i,j,t)$(TIP_t(t) AND (J_C(j) OR J_E(j)) and Z_in(z) and JI(j,i) and JZ(j,z))..
P(z,z,i,j,t) =l= alpha_max(z,z,i,j,t)*F(z,j,t);
EQ3ta(z,zz,i,j,t)$(TIP_t(t) AND J_T(j) and JI(j,i) and JZ(j,z) and JZ(j,zz) and
ZZ_t(z,zz))..
P(z,zz,i,j,t) =g= alpha_min(z,zz,i,j,t)*FT(z,zz,j,t);
EQ3tb(z,zz,i,j,t)$(TIP_t(t) AND J_T(j) and JI(j,i) and JZ(j,z) and JZ(j,zz) and
ZZ_t(z,zz))..
P(z,zz,i,j,t) =l= alpha_max(z,zz,i,j,t)*FT(z,zz,j,t);
EQ4a(z,s,t)$(TIP_t(t) AND S_B_lim(s) and Z_in(z) and SZ(s,z))..
B(z,s,t) =g= beta_min(z,s,t)*SUM(j$(JZ(j,z) and J_B(j) and JS(j,s)),
FB(z,s,j,t));
EQ4b(z,s,t)$(TIP_t(t) AND S_B_lim(s) and Z_in(z) and SZ(s,z))..
B(z,s,t) =l= beta_max(z,s,t)*SUM(j$(JZ(j,z) and J_B(j) and JS(j,s)),
FB(z,s,j,t));
*===== P L A N N I N G =====
EQ5(z,s,t)$(TIP_t(t) and SZ(s,z) AND S_rm(s) AND NOT S_rm_nonrenew(s))..
SUM((i,j)$(J_E(j) and Z_in(z) and IS_rm(i,s) and JI(j,i) and
JZ(j,z)),P(z,z,i,j,t))
+ SUM((zz,i,j)$(J_T(j) and SZ(s,zz) and JI(j,i) and IS_T(i,s) and
JZ(j,z) and JZ(j,zz) and ZZ_t(z,zz)), P(z,zz,i,j,t))
=l= omega(z,s,t);
EQ6(z,s)$(S_rm(s) AND S_rm_nonrenew(s) and SZ(s,z))..
SUM((i,j,t)$(TIP_t(t) AND J_E(j) and Z_in(z) and IS_rm(i,s) and JI(j,i)
and JZ(j,z)),P(z,z,i,j,t)) =l= SUM(t$(ORD(t)=1),omega(z,s,t));
EQ7(z,s,t)$(TIP_t(t) and SZ(s,z))..
B(z,s,t)$S_B(s) =e= b0(z,s)$ (S_B(s) and ord(t)=1) + (1-
eta(z,s,t))*B(z,s,t-1)$ (S_B(s) AND ord(t)>1)

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+ SUM((zz,i,j)$ (J_T(j) and IS_T(i,s) and JZ(j,z) and JZ(j,zz) and
JI(j,i) and ZZ_t(zz,z)), kappa_out(s,i,j)*P(zz,z,i,j,t))
- SUM((zz,i,j)$ (J_T(j) and IS_T(i,s) and JZ(j,z) and JZ(j,zz) and
JI(j,i) and ZZ_t(z,zz)), kappa_in(s,i,j)*P(z,zz,i,j,t))
+ SUM((i,j)$ (J_C(j) and IS_out(i,s) and JZ(j,z) and JI(j,i)),
kappa_out(s,i,j)*P(z,z,i,j,t))
- SUM((i,j)$ (J_C(j) and IS_in(i,s) and JZ(j,z) and JI(j,i)),
kappa_in(s,i,j)*P(z,z,i,j,t))
- zeta(z,s,t) - DISPOSED(z,s,t)$S_DISP(z,s) +
INFEASIBLE(z,s,t)$ (zeta(z,s,t)>0)
+ SUM((i,j)$ (J_E(j) and IS_rm(i,s) and JZ(j,z) and JI(j,i))
,P(z,z,i,j,t));
*===== E C O N O M I C =====
EQ8(z,j)$ (Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j)))..
SUM(t$(TIP_t(t)), W(z,j,t)) =1= 1;
EQ9(z,j,t)$ (TIP_t(t) AND Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j)))..
W(z,j,t) =1= Y(z,j,t);
EQ10(z,j,t)$ (TIP_t(t) AND Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j)))..
W(z,j,t) =g= Y(z,j,t) - SUM(tt$(ord(tt) < ord(t)), W(z,j,tt));
EQ8B(z,s,j)$ (Z_in(z) and JZ(j,z) and JS(j,s) and J_B(j))..
SUM(t$(TIP_t(t)), WB(z,s,j,t)) =1= 1;
EQ9B(z,s,j,t)$ (TIP_t(t) AND Z_in(z) and JZ(j,z) and JS(j,s) and J_B(j))..
WB(z,s,j,t) =1= YB(z,s,j,t);
EQ10B(z,s,j,t)$ (TIP_t(t) AND Z_in(z) and JZ(j,z) and JS(j,s) and J_B(j))..
WB(z,s,j,t) =g= YB(z,s,j,t) - SUM(tt$(ord(tt) < ord(t)), WB(z,s,j,tt));
EQ11(t)$TIP_t(t)..
FA(t) =e= SUM((z,j)$ (Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j))),
epsilon0(z,j,t)*W(z,j,t) + epsilon(z,j,t)*E(z,j,t))+
SUM((z,s,j)$ (Z_in(z) and JZ(j,z) and JS(j,s) and not (J_T(j) or J_E(j) or
J_C(j))), epsilon0(z,j,t)*WB(z,s,j,t) + epsilon(z,j,t)*EB(z,s,j,t));
EQ11t(t)$TIP_t(t).. CT(t) =e= SUM((z,zz,j)$ (TIP_t(t) AND Z_in(z) AND JZ(j,z) and
JZ(j,zz) and J_T(j) and ZZ_t(z,zz)), epsilon(z,j,t)*ET(z,zz,j,t) +
epsilon0(z,j,t)*YT(z,zz,j,t));
EQ11B(t)$TIP_t(t)..
BT(t) =E= SUM((z,s,j)$ (Z_in(z) and JZ(j,z) and SZ(s,z) and J_B(j) AND JS(j,s)),
epsilon(z,j,t)*EB(z,s,j,t));
EQ12(t)$TIP_t(t)..
FC(t) =e= SUM((z,j)$ (Z_in(z) and JZ(j,z) and not (J_T(j) or J_B(j))),
delta(z,j,t)*F(z,j,t));
EQ13(t)$TIP_t(t).. VC(t) =e= RC(t) + PC(t) + IC(t) + TP(t) + DC(t);
EQ14(t)$TIP_t(t)..
PC(t) =e= SUM((z,s,i,j)$ (Z_in(z) and J_C(j) and SZ(s,z) and IS_out(i,s) and
JZ(j,z) and JI(j,i)), ppi(z,s,i,j,t)*P(z,z,i,j,t));
EQ15(t)$TIP_t(t)..
IC(t) =e= SUM((z,s)$ (Z_in(z) and S_B(s) and SZ(s,z)), lambda(z,s,t)*B(z,s,t));
EQ15b(t)$TIP_t(t)..
DC(t) =e= SUM((z,s)$ (Z_in(z) and S_DISP(z,s) and SZ(s,z)),
lambda_disp(z,s,t)*DISPOSED(z,s,t));
EQ16(t)$TIP_t(t)..
RC1(t) =e= SUM((z,s,i,j)$ (Z_in(z) and S_rm(s) and SZ(s,z) and JS(j,s) and JI(j,i)
and JZ(j,z) and J_E(j) and IS_rm(i,s)), psi_z(z,s,i,j,t)*P(z,z,i,j,t));
EQ17(t)$TIP_t(t)..
RC2(t) =e= SUM((z,zz,s,i,j)$ (Z_in(z) and Z_in(zz) and S_rm(s) and SZ(s,z) and
SZ(s,zz) and JS(j,s) and JI(j,i) and ord(zz) ne ord(z) and JZ(j,z) and JZ(j,zz)
and J_T(j) and IS_T(i,s) and ZZ_t(z,zz)), psi_zt(z,zz,s,i,j,t)*P(z,zz,i,j,t));
EQ18(t)$TIP_t(t)..
RC3(t) =e= SUM((zz,z,s,i,j)$ (not Z_in(zz) and Z_in(z) and S_rm(s) and SZ(s,z) and
SZ(s,zz) and JZ(j,z) and JZ(j,zz) and JS(j,s) and JI(j,i) and J_T(j) and
IS_T(i,s) and ZZ_t(zz,z)), psi(zz,z,s,i,j,t)*P(zz,z,i,j,t));
EQ19(t)$TIP_t(t).. RC(t) =e= RC1(t) + RC2(t) + RC3(t);
EQ20(t)$TIP_t(t)..
TP(t) =e= SUM((zz,z,s,i,j)$ (Z_in(zz) and ZZ_t(zz,z) and S_fp(s) and SZ(s,z) and
SZ(s,zz) and JZ(j,z) and JZ(j,zz) and JS(j,s) and JI(j,i) and J_T(j) and
IS_T(i,s)), ex(zz,z,s,i,j,t)*P(zz,z,i,j,t));
EQ21..
OF =e= SUM(t$TIP_t(t), FA(t) + CT(t) + FC(t) + VC(t)) + SUM((z,s,t)$ (TIP_t(t) AND
zeta(z,s,t)>0), 100000*INFEASIBLE(z,s,t));

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MODEL STN_MODEL /ALL/;

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