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Subset Measurement Selection for Globally Self-Optimizing Control of Tennessee Eastman Process ⋆

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Abstract: The concept of globally optimal controlled variable selection has recently been proposed to improve self-optimizing control performance of traditional local approaches. However, the associated measurement subset selection problem has not be studied. In this paper, we consider the measurement subset selection problem for globally self-optimizing control (gSOC) of Tennessee Eastman (TE) process. The TE process contains substantial measurements and had been studied for SOC with controlled variables selected from individual measurements through exhaustive search. This process has been revisited with improved performance recently through a retrofit approach of gSOC. To extend the improvement further, the measurement subset selection problem for gSOC is considered in this work and solved through a modification of an existing partially bidirectional branch and bound (PB^3) algorithm originally developed for local SOC. The modified PB^3 algorithm efficiently identifies the best measurement candidates among the full set which obtains the globally minimal economic loss. Dynamic simulations are conducted to demonstrate the optimality of proposed results.

Keywords: Tennessee Eastman, self-optimizing control, controlled variable, plant-wide control

1. INTRODUCTION

Since published in 1993, the well-known Tennessee Eastman (TE) process (Downs and Vogel, 1993) has been extensively studied by researchers from the field of process control. Various control strategies and algorithms were proposed to address the control problems posed by Downs and Vogel. McAvoy and Ye (1994) used the relative gain array and other controllability analysis tools to configure a basic PID control system, which operates the process around the base case point and met basic requirements posed in the problem. Later, Ricker (1995) identified the optimal steady-state point of process operation, he also presented a well-configured decentralized control structure (Ricker, 1996), which achieved excellent performances for various control tasks. Meanwhile, nonlinear model predictive control (NMPC) algorithm (Ricker and Lee, 1995) was also considered. Jockenhövel et al. (2003) performed dynamic optimization of the TE process using a MATLAB-based OptControlCentre toolbox.

On the other hand, although there are many approaches developed for either control or optimization of the TE process, only a few were concerned with the economic performance by means of selecting controlled variables (CVs), which are of critical importance for a control system. The control system designed by Ricker (1996) controls the active constraints identified from steady state optimization, however, the sensitivity part is not appropriately addressed. Another successful one is the work of Larsson et al. (2001), where the self-optimizing control (SOC) methodology (Skogestad, 2000) was applied to select the best CVs to achieve economic improvements. The SOC is a control strategy that by means of selecting particular CVs, the economic performance of plant operation is automatically "self-optimizing" with an acceptable loss, in spite of disturbances and uncertainties. Such a strategy is particularly appealing for large scale process plants, such as the TE process, where installing and maintaining an extra computationally expensive "real-time optimization" (RTO) layer is unnecessary for economically optimal operation if a well-designed SOC system is implemented.

However, the self-optimizing control structure designed by Larsson et al. (2001) has several limitations. Firstly, only the individual measurements are considered as the CV candidates. It has been well recognized that one achieves better self-optimizing performance by controlling the measurement combinations, because they provide more intrinsic knowledge of the process (Alstad and Skogestad, 2007; Kariwala, 2007; Kariwala et al., 2008; Alstad et al., 2009; Ye et al., 2013). However, an application of measurement combination CVs to the TE process has not yet been

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Table 1. Manipulated variables for TE process

Number	Variable name
XMV(1)	D feed flow
XMV(2)	E feed flow
XMV(3)	A feed flow
XMV(4)	A and C feed flow
XMV(5)	Compressor recycle valve
XMV(6)	Purge value
XMV(7)	Separator liquid flow
XMV(8)	Stripper liquid product flow
XMV(9)	Stripper steam valve
XMV(10)	Reactor cooling water flow
XMV(11)	Condenser cooling water flow
XMV(12)	Agitator speed

reported elsewhere. Moreover, to select out the CVs, the full measurement set was screened largely according to their heuristic judgements of the process characteristics. Although easily understood from an engineer's perspective, too much subjective judgements may omit promising CV candidates that cannot be obviously detected. Since selecting a measurement subset to constitute CV is a combination problem in nature, an exhaustive search way is intractable with substantial measurements. In recent years, a number of algorithms for fast identifying a measurement subset were reported, e.g. the bidirectional branch and bound (BAB) (Cao and Kariwala, 2008; Kariwala and Cao, 2009, 2010) and the mixed integer quadratic programming algorithms (Yelchuru and Skogestad, 2012).

In this study, we consider the measurement subset selection problem for TE process in the framework of SOC. Firstly, we investigate the TE process by applying a new globally SOC (gSOC) method, which approximately minimizes the average loss for all operating conditions for a plant operation (Ye et al., 2015). The new gSOC method is developed in terms of "operating condition" instead of some perturbed "disturbance variables". This method allows us to derive measurement combinations as CVs for the TE process. Then, we investigate the measurement subset selection problem with a modified partially bidirectional branch and bound (PB^3) algorithm, which was earlier employed in local SOC methods based on local average loss minimization. Finally, we implement the derived subsets for gSOC of the TE process through a retrofit approach proposed recently (Ye et al., 2016), dynamic simulations are carried out to validate the optimality.

2. OVERVIEW OF THE PROCESS

2.1 Process description

The plant-wide TE process consists of the following 4 reactions

$$\begin{aligned} A(g) + C(g) + D(g) &\rightarrow G(liq) \\ A(g) + C(g) + E(g) &\rightarrow H(liq) \\ A(g) + E(g) &\rightarrow F(liq) \\ 3D(g) &\rightarrow 2F(liq) \end{aligned}$$

where A, C, D, E are the reactants, G and H are the products and F is the byproduct. Besides, there exists an inert component B in the material circle, which is contained in the feed and removed through purge to maintain inventory balance. The process includes 5 major operating units: the reactor, product condenser, vapor-liquid separator, recycle compressor and product stripper.

Table 2. Measurements for TE process

Number	Variable name
XMEAS(1)	A feed
XMEAS(2)	D feed
XMEAS(3)	E feed
XMEAS(4)	A and C feed
XMEAS(5)	Recycle flow
XMEAS(6)	Reactor feed rate
XMEAS(7)	Reactor pressure
XMEAS(8)	Reactor level
XMEAS(9)	Reactor temperature
XMEAS(10)	Purge rate
XMEAS(11)	Product separator temperature
XMEAS(12)	Product separator level
XMEAS(13)	Product separator pressure
XMEAS(14)	Product separator underflow
XMEAS(15)	Stripper level
XMEAS(16)	Stripper pressure
XMEAS(17)	Stripper underflow
XMEAS(18)	Stripper temperature
XMEAS(19)	Stripper steam flow
XMEAS(20)	Compressor work
XMEAS(21)	Reactor cooling water outlet temperature
XMEAS(22)	Separator cooling water outlet temperature
XMEAS(23–28)	mole fraction of A–F in feed
XMEAS(29–36)	mole fraction of A–H in purge
XMEAS(37–41)	mole fraction of D–H in product

The process includes 12 manipulated variables (MVs) and 41 measurements, as listed in Table 1 and Table 2. For the MVs, they have all been scaled within the 0-100% range, which are considered as valve positions. For the measurements, they are defined with different sampling frequencies and dead time to keep consistence with the industrial practice. An economic index is also introduced, which is composed of the cost/loss of raw materials and energy, see Downs and Vogel (1993) for more details.

2.2 Overview of control structure

In open literature, there have been many control structures developed for the TE process. However, in the remainder of this paper, we will mainly introduce two control systems proposed by Ricker (1996) and Larsson et al. (2001) to get an overview for controlling the TE process. (For the sake of convenience, they will be denoted as "CS_Ricker" and "CS_Skoge" after the corresponding authors respectively. Furthermore, the choice of CV selection is of particular interest in this study and outlined as below.

According to their control policies, the following process variables should be controlled in closed-loops:

(1) Separator level and stripper level. These two liquid levels are integrating variables and have no steady state effects, they must be stabilized in the first place.
(2) Production rate (stripper underflow) and product quality (mole $\%G$ in product). Manufacturing objective defines their targets under different operating modes and specifications, these equality constraints should be controlled to satisfy the targets.
(3) At the optimum, there are 5 active constraints that needs to be controlled at their boundaries: reactor pressure (maximum) and level (minimum), compressor recycle valve (closed), stripper steam valve (closed) and agitator speed (maximum). Ricker (1996) provided detailed physical interpretations why these constraints are active at the optimum.

Above control requirements consume 9 degrees of freedom (DOF) for plant operation. For the remaining unconstrained 3 DOF, Ricker (1996) chose to control the reactor temperature (T_{rct}), $\%A$ and $\%C$ in the feed (more precisely, y_A: the combined $\%A$+$\%C$ and y_{AC}: $\%A/(\%A+\%C)$ in the feed) based on heuristic analysis. Decentralized control structure was considered with appropriately configured loop pairing relationships. Controller tuning is also carried out for all PI controllers, see Ricker (1996) for more detail. The designed control system was very efficient and nicely completed various control tasks proposed by Downs and Vogel (1993) .

On the other hand, Larsson et al. (2001) applied the so-called SOC methodology to improve the operational economic performance for TE process. Their control strategy addressed the situations when the plant is operated under disturbances and different operating conditions (specifically, production rate/throughput change by $\pm 15\%$). A systematic procedure for control structure design and self-optimizing CVs selection was carried out. They found that the most promising CVs for the remaining unconstrained 3 DOF are reactor temperature, recycle flowrate and $\%C$ in the purge. These results were at first surprising and contradicting to engineers' insights of process control, however, the authors had conducted dynamic simulations to demonstrate that their control strategy is viable. As compared to the one in Ricker (1996), the main economic improvements were achieved in the cases of throughput changes.

3. SUBSET SELECTION FOR SOC

3.1 A new SOC method for CV selection

Recently, a new SOC approach for CV selection (Ye et al., 2015), which approximately minimizes the average loss under all operating conditions, has been proposed. Two algorithms were proposed therein to minimize the average loss. Between these two, this work adopts the less rigorous but simpler one, which is based on a convex formulation hence CVs can be solved analytically in terms of various optimal values of a subset of measurements. Furthermore, the sensitivity matrix required in the algorithm is to be evaluated at a single reference point.

Consider the next static optimization problem

$$\min_{\mathbf{u}} J(\mathbf{u}, \mathbf{d}) \quad (1)$$

with measurements

$$\mathbf{y} = \mathbf{f}(\mathbf{u}, \mathbf{d}) \quad (2)$$

where J is the cost function to be minimized, $\mathbf{u} \in \mathbb{R}^{n_u}$, $\mathbf{d} \in \mathbb{R}^{n_d}$, and $\mathbf{y} \in \mathbb{R}^{n_y}$ are the manipulated variables, disturbances, and measurements, respectively. $\mathbf{f} : \mathbb{R}^{n_u \times n_d} \rightarrow \mathbb{R}^{n_y}$ is the measurement model. The objective is to select $\mathbf{c} = \mathbf{H}\mathbf{y}$ as CVs such that the economic loss is minimized under different disturbance scenarios and operating conditions.

Remark: Although the symbol $\mathbf{d}$ is used above to denote disturbances (Ye et al., 2015), the method can be easily extended to any possible operating conditions that cannot be easily described by simple disturbance variables, e.g. a particular case with a pressure setpoint change or a case of instrument failure. Also, since the occurrence of disturbance can be considered as a type of operating condition, we will refer the term "operating condition" to all possibilities afterwards, without loss of generality.

A brief description of the algorithm (Ye et al., 2015) involves the following steps:

(1) For all N operating conditions, say $\mathbf{d}_{(i)}, i = 1, ...N$, the cost function J is minimized using an optimization solver. The optimal values of measurements, $\mathbf{y}_{(i)}^{\text{opt}}$ are obtained and form a matrix as

$$\mathbf{Y} = \left[\mathbf{y}_{(1)}^{\text{opt}} \; \mathbf{y}_{(2)}^{\text{opt}} \; \cdots \; \mathbf{y}_{(N)}^{\text{opt}} \right]^{\text{T}} \quad (3)$$

Here, the measurement vector $\mathbf{y}$ is defined to include an artificial measurement: constant 1, so that the setpoints of all final derived CVs are 0.

(2) In the presence of measurement noises, construct an extended matrix $\tilde{\mathbf{Y}}$ as

$$\tilde{\mathbf{Y}} = \begin{bmatrix} \frac{1}{\sqrt{N}} \mathbf{Y} \\ \mathbf{W}_n \end{bmatrix} \quad (4)$$

where $\mathbf{W}_n$ is a diagonal matrix with its diagonal elements as the error magnitudes of each measurement.

(3) Choose a particular operating point as the reference point, the gain matrix of $\mathbf{y}$ with respect to the MVs is evaluated as $\mathbf{G}_{y,r}$.

(4) Following above steps, an approximated global average loss L_{av}, is expressed as

$$L_{\text{av}} = \frac{1}{2} \| \tilde{\mathbf{Y}} \mathbf{H}^{\text{T}} \|_{\text{F}}^2 \quad (5)$$

by enforcing $\mathbf{H}$ satisfying $\mathbf{H}\mathbf{G}_{y,r} = \mathbf{J}_{uu,r}^{1/2}$.

(5) The optimal $\mathbf{H}$ minimizing L_{av} is analytically given as

$$\mathbf{H} = \mathbf{J}_{uu,r}^{1/2} (\mathbf{G}_{y,r}^{\text{T}} (\tilde{\mathbf{Y}}^{\text{T}} \tilde{\mathbf{Y}})^{-1} \mathbf{G}_{y,r})^{-1} \mathbf{G}_{y,r}^{\text{T}} (\tilde{\mathbf{Y}}^{\text{T}} \tilde{\mathbf{Y}})^{-1} \quad (6)$$

3.2 PB^3 algorithm for subset selection

For the subset selection problem, Kariwala and Cao (2010) has developed a PB^3 algorithm based on the local average loss criterion. In the PB^3 algorithm, candidate measurement subsets are divided into branches and evaluated against upwards and downwards pruning criteria. Branches, which satisfy either upwards or downwards pruning criteria will be fixed or removed from candidate list, respectively. In this way, most non-optimal candidate subsets will be eliminated without further evaluations so that the optimal subset can be efficiently identified. The reader is referred to Kariwala and Cao (2010) for more detailed description of this algorithm.

By making a comparison of the gSOC method (Ye et al., 2015) to the local formulation (Alstad et al., 2009; Kariwala et al., 2008), one finds that the approaches are equivalent except for that an intermediate matrix ($\tilde{\text{Y}}$ in gSOC and Y in loacl SOC) is constructed differently, see these references for more details. Therefore, the partially bidirectional branch and bound (PB^3) algorithm developed for subset selection based on a local SOC method (Kariwala and Cao, 2010) is modified to fit the gSOC method.

Table 3. Optimization results

	Cost[\$/h]	y_A[%]	y_C[%]	XMEAS(9) $^{\circ}C$
normal	114.01	32.21	18.75	122.9
IDV(1)	111.27	32.35	19.69	123.0
IDV(2)	169.03	30.47	17.94	124.2
throughput +15%	140.55	33.45	19.68	124.3
throughput -15%	91.01	30.80	17.50	121.6
40 G/ 60 H	129.07	32.92	18.93	123.4
rct press 2645 kPa	134.93	32.01	18.82	123.6

4. SUBSET SECTION FOR THE TE PROCESS

4.1 Optimization for operating conditions

Firstly, 9 CVs, including two liquid levels and 7 equality constraints (see Section 2), should be controlled. These CVs are selected with the same reasons as in CS_Ricker and CS_Skoge. This leaves 3 CVs to be selected for SOC.

Originally, Downs and Vogel (1993) defined 20 disturbance scenarios, IDV(1-20), among which Larsson et al. (2001) considered IDV(1) and IDV(2) (changes in A/C ratio and B composition in C feedstream, respectively), because other disturbances are either with no steady state effects or too severe to be handled in a simple control structure. Besides, they also considered the situations when the set-point of production rate (throughput) is changed by ±15%. In this study, we additionally incorporate two situations as posed by Downs and Vogel (1993): (1) when the product mix changes from 50 G/50 H to 40 G/60 H; (2) a step change of set-point for reactor pressure to be 2645 kPa. Therefore, there will be 7 operating conditions in total (including the normal operating condition) investigated in this study.

Following the gSOC method, firstly, the economic index J is minimized for all 7 operating conditions using a Genetic Algorithm. Based on CS_Ricker, the set-points of y_A, y_{AC} and XMEAS(9) are solved to minimize J, i.e.

$$\mathbf{u} = [y_A \; y_{AC} \; \text{XMEAS(9)}]^T \tag{7}$$

in the formulated optimization problem.

Results of the minimal cost and optimal decision variables are summarized in Table 3. Meanwhile, optimal values of all 41 measurements are also obtained for these 7 cases (numerical values are not shown here). Besides, the magnitudes of the measurement errors are also estimated from the process variables. The sensitivity matrix $\mathbf{G}_y$ and the Hessian J_{uu} are evaluated at the normal condition with finite difference method, by perturbing the set-points of y_A, y_{AC} and XMEAS(9) while keeping other active constraints controlled.

4.2 Subset selection results

Measurement candidates. In principle, both the output measurements and input MVs can be considered as candidates for constituting CVs. This gives us a set of 42+12=54 measurements. However, there have been 9 loops closed with variables maintained at constants, hence they cannot be used as measurement candidates, these are: XMEAS(7,8,12,15,17,19,40) and XMV(5,9,12), see Section 2. Note, XMEAS(19) (steam flow) and XMV(9) (steam valve) are actually the same variables. Therefore, we are left with 44 candidate measurements which are, however, still substantial and intractable to search exhaustively.

For SOC purpose, Larsson et al. (2001) used heuristic approach together with substantial quantitative analysis to eliminate undesired CV candidates. However, this could be time consuming and very much rely on the designer's insights toward the process under consideration. In the sequence, the modified PB^3 algorithm is applied based on the global average loss criterion.

The tests are conducted on a Windows 7 SP1 operating system with i5 @3.3GHz CPU and 8 GB RAM using MATLAB R2013a. The sizes of measurement subset $3 \leq m \leq 44$ are considered, all the promising subsets are automatically picked in a short period of time by using the PB^3 algorithm. The computation times (averaged for 100 times) are plotted in Figure 1 (a), where the largest time is 3.14 s occurring at m=15. The minimal average loss as m ranging from 3 to 44 is illustrated in Figure 1 (b). As indicated evidently in the figure, a choice of $m = 5$ or 6 can be considered to make a good balance between the economic performance and CV complexity.

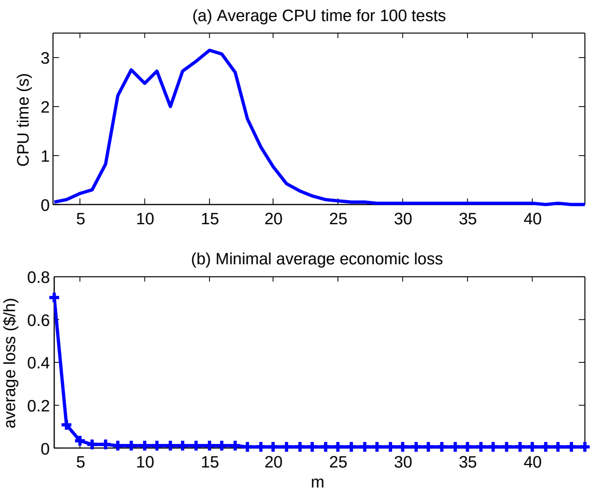

Fig. 1. PB^3 algorithm for subset selection against m

The average losses of promising measurement subsets for $m = 3-6$, together with those of CS_Ricker and CS_Skoge, are shown in Table 4. First of all, when $m = 3$, the average losses of CS_Ricker and CS_Skoge are calculated as 1.4615 and 0.9083, which are significantly larger than the minimal one obtained in this study (0.7001). The best subset is XMEAS(9,20,31) (Reactor temperature, compressor work, mole fraction of C in purge). Interestingly, this was identified by Larsson et al. (2001) as the second best choice, which in their paper gave 0.1 more total loss as compared to the best one, XMEAS(5,9,31). The big loss of controlling XMEAS(5,9,31) could be due to several reasons, e.g., two additional operating conditions were not included in CS_Skoge. Actually, we have found that CS_Skoge gives a quite big loss for the operating condition when reactor pressure is set to be 2645 kPa. Moreover, the measurement errors are not considered therein.

Secondly, MVs are rarely included except for that XMV(6) (the purge valve) is used when m=5. Besides, one sees that the promising subsets contain many composition variables

Table 4. Promising measurement subsets

	XMEAS index	XMV index	average loss
m=3	[9, 20, 31]	-	0.7001
	[21, 31, 33]	-	0.7211
	[31, 33, 34]	-	0.7518
	[28, 31, 34]	-	0.7576
(CS_Ricker)	[9, 23, 25]	-	1.4615
(CS_Skoge)	[5, 9, 31]	-	0.9083
m=4	[25, 29, 34, 38]	-	0.1063
	[23, 25, 34, 38]	-	0.1081
	[29, 31, 34, 38]	-	0.1101
m=5	[9, 29, 31, 38]	[6]	0.0328
	[9, 23, 31, 38]	[6]	0.0356
	[9, 10, 29, 31, 38]	-	0.0359
m=6	[4, 18, 20, 30, 31, 34]	-	0.0169
	[4, 18, 20, 24, 31, 34]	-	0.0177
	[4, 18, 20, 28, 30, 31]	-	0.0179

(XMEAS index≥23), which are generally key variables in a typical chemical process. Among them, XMEAS(31,34,38) (mole fraction of C and F in purge, mole fraction of E in product) are frequently contained, indicating that they are important variables for optimal operation. Note, XMEAS(31) has been identified in CS_Skoge and controlled, however, XMEAS(34,38) were omitted but considered as good measurements in this paper.

4.3 Dynamic simulations

For dynamic simulations, the two best subsets in the cases of $m = 3$ and 6 are tested to validate the results obtained above: (1) XMEAS(9,20,31); (2) XMEAS(4,18,20,30,31,34). Since CS_Ricker was so well-configured in stabilizing the plant operation and completes fundamental control tasks, it is used as a basis to control the obtained self-optimizing CVs by adjusting the set-points of y_A, y_{AC} and XMEAS(9). The optimal combination matrices for the two alternatives are calculated as

$$\mathbf{H}_1 = \begin{bmatrix} -65.8 & 0.118 & 0.199 & -0.192 \\ -8.7 & 0.021 & -0.010 & 0.692 \\ -123.3 & 1 & 0 & 0 \end{bmatrix}$$

$$\mathbf{H}_2 = \begin{bmatrix} -43.9 & 0.98 & 0.39 & 0.09 & -0.32 & -0.43 & -0.71 \\ -12.6 & 0.14 & 0.17 & -0.03 & 0.05 & 0.64 & -0.27 \\ -29.5 & 0.57 & 0.22 & -0.003 & 0.16 & 0.16 & 0.87 \end{bmatrix}$$

Note these matrices are transformed by multiplying a non-singular matrix for steady-state decoupling of CVs.

In the dynamic simulations, 3 PI controllers are tuned to control the self-optimizing CVs. Firstly, the two alternatives are tested for all the 7 operating conditions with a duration of 150 h. As a comparison, CS_Ricker and CS_Skoge are also tested in the same fashion. With the system states initially as steady state values for the normal condition, the economic performances for these 4 control systems are obtained in Table 5, where the achieved minimal loss is in bold face (for dynamic performance in the presence of measurement noises, we consider a difference of ±0.1 average loss is negligible).

Among 7 operating conditions tested, the two alternatives designed in this paper achieve significant improvements over CS_Ricker and CS_Skoge. For example, the Alternative 1 (m=3) reduces the loss mainly in the operating

Table 5. Average cost [$/h]

	CS_Ricker	CS_Skoge	m=3	m=6
normal	**114.00**	**113.94**	**114.00**	114.14
IDV(1)	111.62	**111.49**	**111.59**	111.79
IDV(2)	171.85	170.35	170.00	**168.51**
throughput +15%	147.15	143.15	143.05	**141.72**
throughput -15%	93.41	**90.35**	90.79	**90.35**
40 G/ 60 H	130.85	**130.60**	**130.63**	**130.68**
rct press 2645 kPa	137.68	142.89	139.74	**137.36**
sum	906.56	902.77	899.8	**894.55**

conditions of thourghput change by ±15% as compared to CS_Ricker. Although the same improvements can be achieved by CS_Skoge, Alternative 1 is able to maintain the loss small (139.74) even when the reactor pressure is set to be 2645 kPa, in which case CS_Skoge gives a big loss (142.89). The economic performance is even better for Alternative 2 by controlling combinations of 6 measurements. The control system archives 5 minimal loss out of 7 operating conditions. In the other 2 cases (normal and IDV(1)), Alternative 2 also gives small losses although it is not the best anyway. Finally, based on the calculated overall economic losses, the 4 control systems are ranked as Alternative 2 (894.55)> Alternative 1 (899.8)>CS_Skoge (902.77)> CS_Ricker (906.56), where the symbol ">" is read as "better than".

In the following, we investigate an arranged series of operating scenario as: (1) Initially, the system is operated under normal condition; (2) At 10 h, the setpoint of production rate (throughput) is increased by +15%. To avoid abrupt fluctuation, the set-point change is ramped within a period of 10 h (10 h - 20 h); (3) At 80 h, the production rate is reset to normal condition, simultaneously, the set-point of reactor pressure is changed from 2800 kPa to 2645 kPa. Similarly, both the set-point changes are ramped within a period of 10 h.

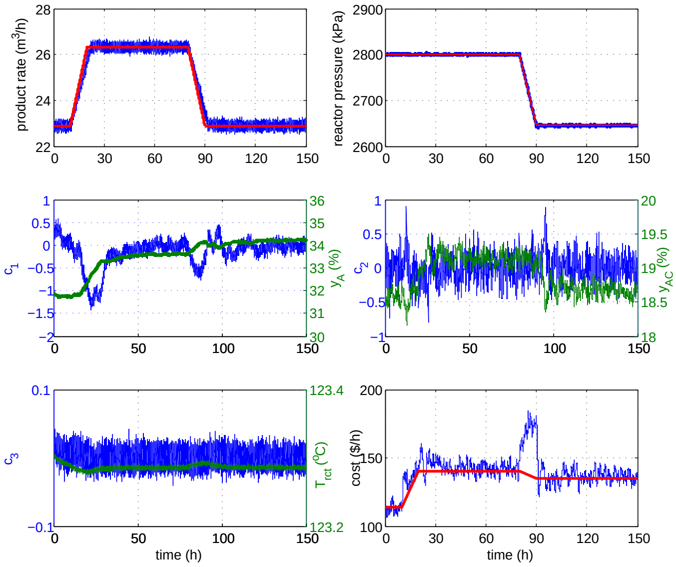

Fig. 2. Dynamic performance of Alternative 1

Both the two schemes work nicely for the operating condition switching, as indicated in the top two sub-figures, the setpoints of production rate and reactor pressure (red line) are tracked quickly and smoothly. This is because the con-

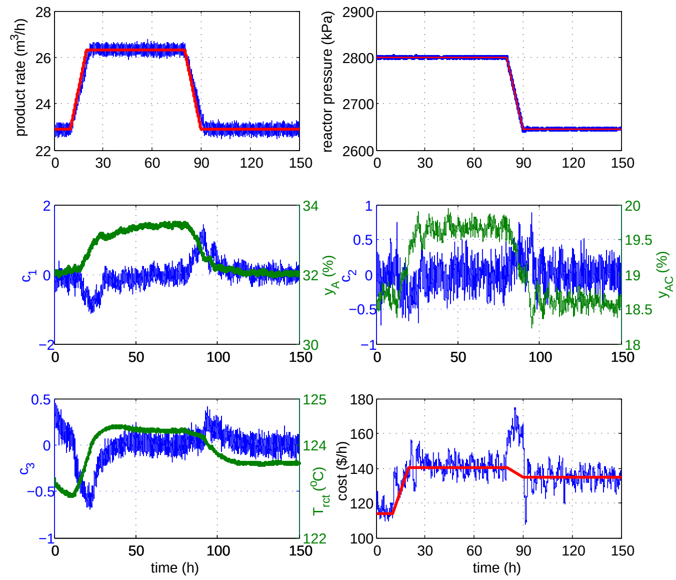

Fig. 3. Dynamic performance of Alternative 2

trol system is directly configured upon CS_Ricker with the lower regulatory controllers unchanged, hence the merits of CS_Ricker are preserved. However, by maintaining the self-optimizing CVs around their constant setpoints (all 0) in added upper control layer, the setpoints of lower loops are automatically adjusted accordingly (green line). Note, they are adjusted to different positions for Alternative 1 and 2 because different self-optimizing CVs are adopted. As expected, the economic cost (right bottom sub-figure) is operated around the minimum (red line) in all the simulation time for both cases, thus indicating good economic performances. Although visually hard to tell the difference, the overall economic costs are calculated as 20965 $ and 20641 $ for Alternative 1 and 2, respectively.

Finally, the same arranged series of operating scenario is tested for CS_Ricker and CS_Skoge. The obtained results give their overall economic costs as 21088 $ and 21195 $, which are higher than the control systems in this paper. Therefore, the proposed control strategy would be more favored by an economy-sensitive designer.

5. CONCLUSIONS

In this paper, we investigate the measurement subset selection problem for self-optimizing control of the TE process. A PB^3 algorithm is used to efficiently screening the full measurement set based on a global average loss criterion. For the TE process, it was found that using 5 or 6 measurements makes a good compromise between the economic performance and CV complexity. Also, it was revealed that the composition variables are key variables for optimal control of the TE process. Based on the subsets obtained, two alternatives were tested through dynamic simulations, their optimality was verified with comparisons to the control systems designed by Ricker (1996) and Larsson et al. (2001).

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