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Factory Eco-Efficiency Modelling: Data Granularity and Performance Indicators

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Abstract

Eco-efficiency is becoming an increasingly important performance measure. Currently manufacturers rely on reactive methods such as auditing for assessment. There are still significant theoretical and practical barriers including a lack of knowledge regarding the selection and composition of appropriate data granularities, model quality to improve decision making, and split incentives between facilities and manufacturing asset management. The purpose of this paper is to show the application of an eco-efficiency modelling framework in the case of a fast-moving consumer goods factory. The framework composes resource and production data. These are analysed with respect to three data granularity factors, asset subdivision, time-step, and resource magnitude. Modelling is used to represent asset eco-efficiency across available subdivisions using performance indicators.

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1. Introduction

Manufacturing sector demands for energy and material resources are increasing. Presently manufacturing consumes over 35% of the global energy, whilst emitting 17% of global greenhouse gasses [1]. Public policy has brought eco-efficiency to the forefront of global sustainability strategies for reducing energy, material consumption and carbon emissions by 2050. Incentives to increase the use of renewables can be easier realised and augmented by

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becoming eco-efficient. Eco-efficiency could save more than one-fifth of projected manufacturing energy and material demands [2]. For these reasons factory operational eco-efficiency is becoming an important performance measure. Its indicators are regularly used alongside those of productivity, cost, quality, health and safety.

Moves toward improving factory eco-efficiency are being driven by reductions in resource use [3]. Early interventions seek to reduce energy and materials used in localised areas, such as manufacturing cells [4]. However, there is paucity of literature on the combining of manufacturing, utility and facility assets. In particular, there is little consideration for the relationship between operational assets, data granularity and eco-efficiency performance indicators. A factory eco-efficiency modelling framework based upon data-granularity factors is justified using literature. It is then applied to an international fast-moving consumer goods manufacturer's resource and production data. Eco-efficiency modelling results are discussed with conclusions provided on the framework's applicability.

2. Literature Review

2.1. Factory Asset Subdivisions

Examining factories as an integration of manufacturing, utilities and facilities is necessary to consider the distribution of resources, and how these relate to technical assets within a factory site [5]. Data granularity refers to the extent to which a factory's resource data can be isolated into distinguishable pieces. Therefore, subdividing logged time-steps and resource magnitude data by linking to factory technical assets is logical.

However, factory modelling brings with it the complexity of composing a variety of asset subdivisions with discrete resource time-steps and magnitudes. Facilities consist of core manufacturing and auxiliary (e.g. kitchen) zones, which pull resources from utility assets. Data composition is a crucial pre-requisite for understanding the interrelationship between these assets. All asset subdivisions should be linked to time-step and magnitude granularity factors to help visualise asset performance. Presently, there are gaps in eco-efficiency and modelling literature on data composition and asset modelling with appropriate indicators using data granularity factors.

Beyond Lean there is little to support the analysis of resources across subdivisions. Current modelling tools and techniques are informed by detailed knowledge of narrow functional boundaries [6]. This makes their applicability limited when modelling across different asset subdivisions, where analyses of individual asset configurations require integration within the wider factory system. A means for understanding factory eco-efficiency [7] through data granularity factors, including the subdivision of technical assets, is required. The framework develops knowledge in this area through data composition within and across asset subdivisions. Analysis of subdivisions is performed by linking with eco-efficiency performance indicators. Framework models can be assembled at selected subdivisions appropriate to organisations eco-efficiency objectives with the ability to measure asset eco-efficiency [8].

2.2. Eco-efficiency Performance Indicators and Magnitudes

There are recognised examples of eco-efficiency that address the magnitude of resource impacts conceptually. Examples include Industrial Ecology, Reduce, Reuse and Recycle and Green-Supply Chain Management. However, quantifying eco-efficiency for energy and material resources flowing through a factory system is difficult to evaluate using conceptual approaches alone. Despite widespread dissemination of existing eco-efficiency improvement initiatives, and reported studies exemplifying economic [9] and environmental [10] benefits, implementation barriers and performance variation still continue [11]. Examination of the literature suggests a lack of rigour and repeatability in the application of modelling, and the selection of performance indicators for modelling resource magnitudes at different time-step rates, across appropriate subdivisions.

Contrary to eco-efficiency literature, operations management provides established improvement methods for process optimisation. Methods include six sigma zero-defects, TQM plan-do-check-act, and Lean value stream mapping, detail behaviours for standardising productivity improvement efforts. Indicators in this area focus on production inventory, quality and lead time [12]. Operations management literature shows that performance improvement efforts are made on process, labour and capital productivity, of which resource improvements are a beneficial side effect. Material flow analysis and life cycle assessment of product resources exist. Although structured by eco-efficiency indicators and beneficial from a CSR perspective [13], their models have a limited ability to capture resource magnitudes dynamically. This makes their applicability questionable at some subdivisions such as those of manufacturing cells, single machine and machine processes due to their interaction over time. These subdivisions require dynamic models of resource distributions, with per-minute to per-second time-steps to help diagnose asset performance, and identify improvement opportunities.

Many performance indicators are applicable at multiple asset subdivisions. However, some performance indicators, such as energy per unit, are more applicable at manufacturing cells and single machine subdivisions [14]. Whereas energy mix and power factor are more applicable at facilities and facility zones, when a number of different assets require eco-efficiency analysis [15]. Facility assets (e.g. air conditioning) operate in relation to manufacturing asset requirements (e.g. shop floor temperature and humidity). Utility assets may also share resources with building and manufacturing assets (e.g. hot/cold water circuits, compressors, steam pumps etc.). Therefore, attention in the proposed model is given to the impact and relationship of resource magnitudes across subdivisions. Once resource magnitudes are composed in the modelling environment they are coupled with performance indicators to show their impact on selected subdivisions.

2.3. Modelling and Time-steps

Modelling is widely used within facilities, utilities [16] and manufacturing [17] design and operations. However, modelling in these domains typically favour point-solutions for single assets. This restriction in scope is predominately caused by the compatibility of time-step measurements for selected assets. Modelling time-steps for assets independently can lead to complications in the control of factory assets across subdivisions [18], and increase the potential of sub-efficient results [19]. Making selection of an appropriate tool more complicated when modelling multiple asset subdivisions with measurements logged at different time-steps [20].

Facility assets are modelled within tools like IES<VE>, MicroStation and Ecotect. These tools focus on the eco-efficiency of assets during the design and construction phases (e.g. embodied carbon) of a facility's lifecycle, and not on the performance of facility assets throughout operations. Therefore, time-steps for these assets have a relatively coarse per-month granularity specific for designing and constructing building fabric eco-efficiently. Manufacturing modelling tools on the other hand, focus on operational eco-efficiency. These normally use finer per-minute time-steps to assess asset details such as processing costs, cycle-times and queue buffering. This distinction in time-step granularity is important for linking between operationally-focused subdivisions. Additionally, these modelling tools are able to simulate both continuous flows and discrete events, making them useful for modelling continuous resources (e.g. water) alongside discrete manufacturing (e.g. machining), utility (e.g. pump) and facility (e.g. lighting) assets.

3. Factory Eco-Efficiency Modelling Framework

As progress is made in eco-efficiency, advances become more challenging. To accommodate further opportunities, an expansion of scope integrating resources across functional boundaries of manufacturing, utilities and facilities assets is necessary (figure 1) [21]. The framework achieves this in a dynamic way through modelling and simulation.

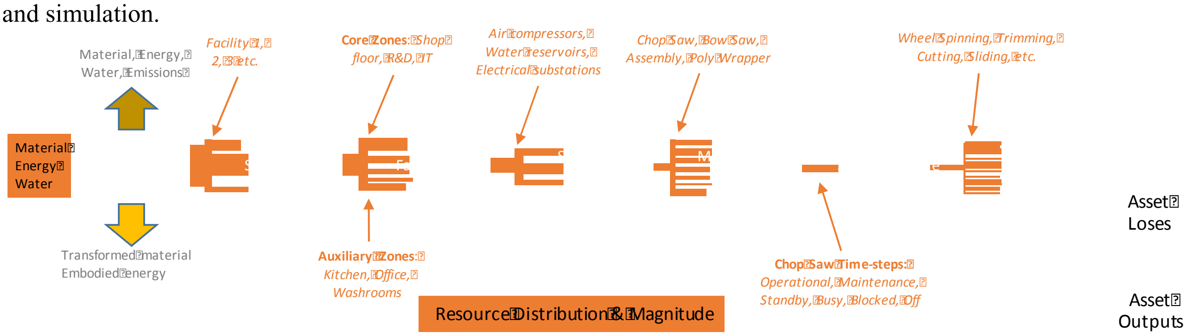

Figure 1: Framework schema integrates asset subdivision with resource time-step and magnitude (adapted from [21])

3.1. Framework Conceptual Model and Application Method

A conceptual model [21] is used to analyse asset resource consumption and improve operational eco-efficiency from the factory site boundary to machine processes. Each subdivision of the framework considers assets at greater detail by progressively modelling finer data granularities. All subdivisions modelled focus on the dynamic behaviour of system inputs, outputs, controllers and losses to show asset eco-efficiency, based upon resource magnitude and time-step granularity factors.

Application of the framework through modelling is integrated as part of a normal feedback process in order to minimise impact when being used by operations personnel. It can use existing or projected resource, production and cost data, which promotes framework modelling as a tool for continuous improvement [22]. Framework application (section 4) shows results of modelling per-hour time step data, measured at facility zones, single zone utilities and manufacturing cell subdivisions. These subdivisions are systemically modelled to analyse the eco-efficiency performance of associated assets. Detailed descriptions and visualisations of both the conceptual model and modelling method are given in earlier framework development and testing papers [21], [23] (see figure 1 for a simplified representation of the framework).

3.2. Framework Justification

Modelling guidance on the applicability of specific time-step granularities to consistently compose, model and indicate eco-efficiency is still required. The proposed framework needs to consolidate subdivisions with resource data at all available time-steps. This helps quantify asset eco-efficiency, and produces a comprehensive understanding of the factory system, in which the modelled assets operate [24]. To develop knowledge in the area of data granularity the factory eco-efficiency modelling framework must apply a systematic data composition and modelling approach based upon asset subdivisions. This helps modellers' move beyond current-tendencies of developing localised point-solutions, specific to single asset's time-step. Framework modelling results needs to measure and determine improvement opportunities at single or multiple time-step granularities, based on the application of best practices from specific industries [25]. Framework models must incorporate the evaluation of material, energy and water through the use eco-efficiency indicators, which measure resource impact over time to improve performance of factory asset subdivisions.

4. Framework Application

The framework was applied within the company's main factory at site, facility, single zone utility and manufacturing cell subdivisions. The company was interested in understanding energy efficiency comparatively across their organization using the power factor performance indicator. This eco-efficiency performance variation is done by benchmarking the five sites against the main. All factories exist in the same geographic region and produce a similar volume of consumer goods.

The company were able to adapt the framework in order to help them plan and implement a method for achieving their organisational eco-efficiency objectives. The following framework interventions are required to help indicate opportunities and improvements using a top-down method.

1. Electrical efficiency (power factor indicator):
    a. Comparison of power factors across sites
    b. Power factor improvement potential
2. Methane efficiency (heating degree hours indicator):
    a. Main facility central heating analysis
    b. Correlation with heating degree hours
3. Energy profile (consumption/production indicator):
    a. Single zone utility air conditioner efficiency
    b. Manufacturing cell energy usage simulation
    c. Manufacturing practice library recommendations

The factory site subdivision is the entry point top-down analysis; it is defined as the boundary, enclosing all assets being analysed. This high-level view of eco-efficiency has been undertaken for the purposes of comparison and for prioritising which factory of the six should be considered at more detailed subdivisions. Analysis of the main at a facility level was then carried out on the central heating assets to show their methane consumption efficiency in comparison to the heating degree hour indicator, extracted from historic weather pattern data to show the R^2 Correlation. Lastly, an example of the simulation output showing the energy profiles of the largest main consumer a painting manufacturing cell, and its air conditioning utility is provided. This simulation model was built using per hour time step data for production and electricity consumption. Results presented also highlight how the manufacturing practice library could help to improve the eco-efficiency of the factory system.

5. Framework Analysis

5.1. Factory site subdivision:

Power factors have been derived from active and apparent energy data as measured hourly in the factory over 2 years' production periods. Pareto analysis (Figure 2) of electrical efficiency shows that the largest energy efficiency opportunities exist in Site 1 (Main) and Site 2. Electrical efficiency analysis for 6 factories shows that site 6 and site 5 are the best performing with 99.7%, and 99.6% inside the >=0.9 power factor range. Power factor is a ratio in kW of (active – reactive) energy/apparent energy to calculate the cos phi angle of effective energy efficiency. Data has been captured using energy loggers for per-hour analysis of the factory sites across 365 days, falling into a 0.00 to 1.00 cos phi, range no data can be calculated outside of this range.

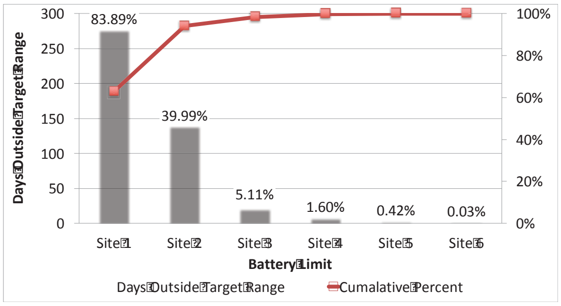

Figure 2: Power factor improvement potentials for six sites

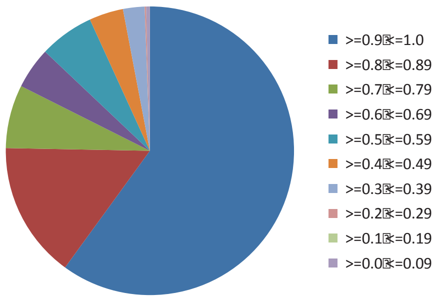

Figure 3: Per-hour for factor value count for site 2

The largest opportunity for efficiency improvement lies within Sites 1 and 2, with 83.8% and 39.9% respectively, recorded outside of >=0.9 power factor range. Detailed analysis (e.g. Figure 2) of these two sites shows that although site 2 has a larger range of power factors, which if improved could result in large savings. Site 1 has a smaller range of power factors, with 260 days recorded within the >=0.8 <=0.89 interval.

This suggests that any small improvements in energy practices (such as turning off large energy users between shifts) will significantly improve the overall electrical efficiency. However, both of these recommendations are contingent on level of production, the age of utility/manufacturing assets and the size of the plant. A series of eight recommendations were provided to the organisation for implementation such as changing to low-loss transformers (e.g. Wilson Transformer). High-volume manufacturers will see immediate energy savings (lowest combined losses of 70% saving on standard transformers), with a typical payback period is 18-28th months.

5.2. Site facilities subdivision:

Analysis of methane consumption and heating degree hours for central heating assets in Site 1 (figure 3) is the most methane efficient facility of the six within the geographic region. Heating degree hours is a measurement designed to measure the demand for energy needed to heat a facility. It is derived from measurements of outside air temperature (weather station is located within boundary of sites). The heating requirements for a given building at a specific location are considered to be directly proportional to the number of heating degree hours at that location. With an R^2 value of 0.635 at this subdivision, some improvements are required. However, at more detailed subdivisions such as the manufacturing cell methane consumption shows it is well monitored and controlled.

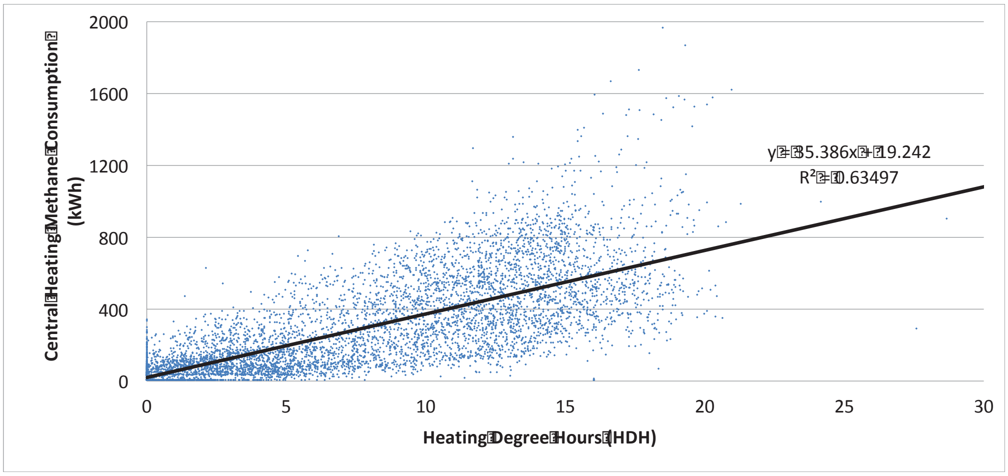

Figure 4: Site 1 facility shows a positive correlation with an R^2 of 0.6

5.3. Single zone utilities subdivision:

A profile of AC energy consumption is modelled for the 2013-2014 operational period. An example from August is shown (figure 5), as it gives an indication of operational, baseline during a shut-down, and ramp/ramp down periods. The blue bars represent energy captured during the 2013-14 operational period. This is plotted using a per-hour granularity over the period of one month to show the dynamics in the energy consumption of the air conditioning asset. To help guide the analysis a comparison with 2012-2013 data is presented using purple, blue, green lines, which represent the maximum, average and minimum energy usage.

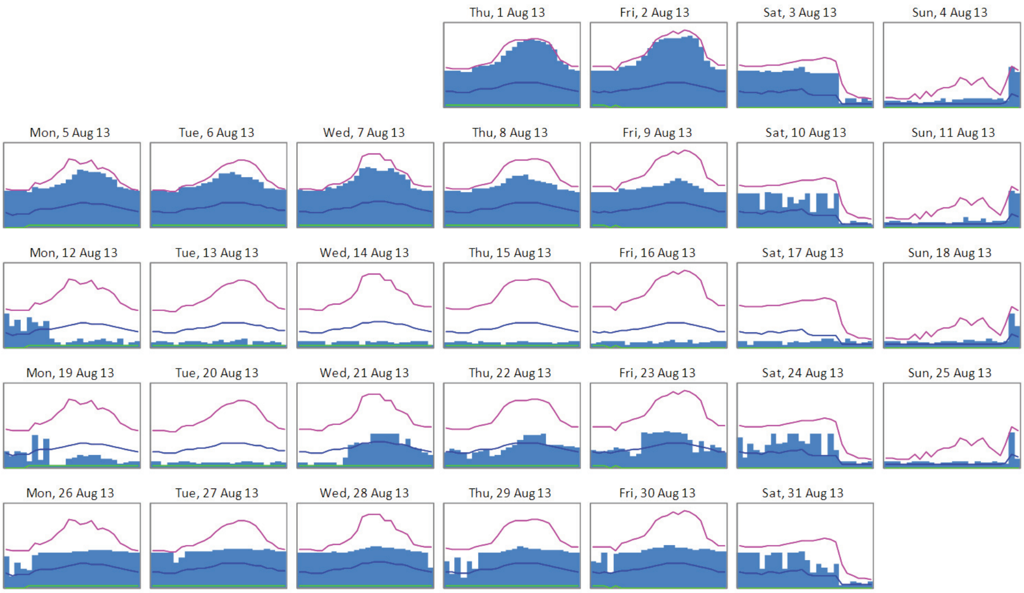

Figure 5: Air conditioning utility MIN, AVG and MAX values for comparison

All chart scales run from 0 to 390 kW (average power over hour interval). Maximum, average, and minimum profiles are also included to show how closely linked each day is to these ranges. Some interesting patterns are noticeable from this analysis such as peaks in consumption, maintenance periods and asset startups. When discussed with process experts these were justified as a maintenance period and automated controllers/switches. One example is the how much a specific cell (e.g. paintshop) will use during a startup, which can lead to recommendations to change offset points in the startup process to minimise the energy impact on the AC assets.

5.4. Manufacturing cells subdivision:

A manufacturing cell energy profile (figure 6) is presented from a simulation model created using per-hour data for the 2013/14 operational period. The blue bars represent production volumes. Red line is electricity, and green methane. These simulations allow testing of "what-if" scenarios and the application of manufacturing tactics which attempt to minimise resource consumption without impacting production throughput.

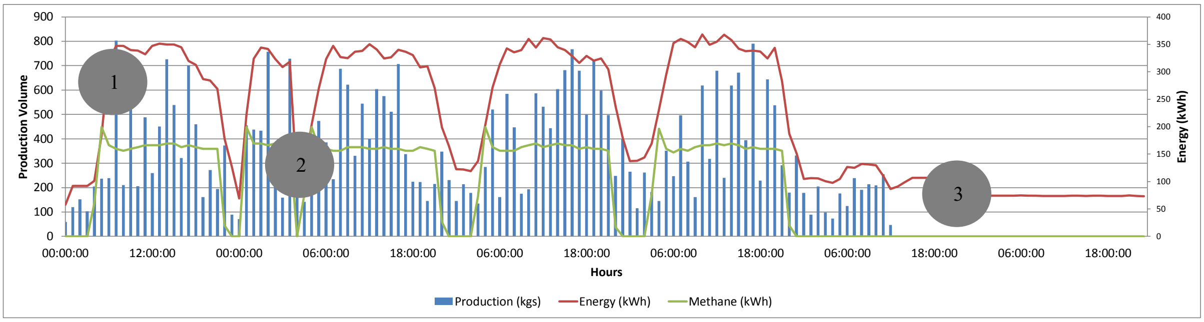

Figure 6: Manufacturing cell production, electrical energy and methane profiles

Bullet 1: Highlights electricity and gas resource peaks. Application of "Resource Reduction" tactics within the simulation model could help test potential changes in the effectiveness of set-points.

Bullet 2: Highlights electricity consumption in production troughs. Application of "Prevention" tactics such as realignment to suit supply, usage and set-points, and simulating energy-mass balance tests, improve efficiency

Bullet 3: Highlights base load electricity in zero production. Application of "Loss Reduction" tactics such as adjustment/substitution of facility zone and process controllers based on mismatch can be applied to assets.

6. Framework Applicability and Case Conclusions

The framework has been designed to further operational eco-efficiency modelling knowledge using data granularity. It combines factory technical assets with resources, and eco-efficiency indicators, within quantitative models. The reason for undertaking this work comes from the realisation that the quality of technical interventions in factories is governed by the coherence of data granularity, the types of models developed and selection of appropriate eco-efficiency indicators/visualisations that help inform decision making. Data granularity factors for asset subdivision, time-step and resource magnitude can be used to develop cursory and detailed models for any size and sector industry. This paper has shown that the framework is useful for developing models at both the depth and breadth requirements needed by the organisation. It is important to note that industrial processes can often dwarf all other types of energy consumption in a facility. If a specific facility within the site has processes or items of equipment that consume a lot of energy, even small changes to the way that they are operated can often make a big difference to the energy bill.

Analysis of the site subdivision has shown that there are a number of opportunities to improve electrical efficiency. Specifically, the largest opportunity for efficiency improvement exist in Site 1 (the main factory) and Site 2, with 84% and 40% respectively, recorded outside of the required power factor range. Implementations of the recommendations on these sites will be the most beneficial in regards to environmental and economic targets.

Methane consumption at a manufacturing cell level appears to be well monitored and controlled. However, analysis of central heating assets shows that improvement opportunities exist (Site 1 R^2 value of 0.6 justifies this statement). There is scope to implement current recommendations (only an example of the recommendations are provided in the present paper) and identify further improvements, through further collaborative work. The simulation of manufacturing cell has yielded recommendations for the organisation based upon the application of tactics from a library of practices. These can also be tested in the simulation model, in order to assess the risks and rewards associated with each recommended tactic adjustment and/or substitution, prior to implementation. This work contributes new knowledge to the area of industrial sustainability by showing how top-down analysis using the framework indicators can be used to model eco-efficiency.

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