

13th Global Conference on Sustainable Manufacturing - Decoupling Growth from Resource Use

Factory eco-efficiency modelling: framework application and analysis

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Eco-efficiency is becoming an increasingly important organisational 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 data granularity, model results quality 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 furniture-manufacturing 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. This paper contributes to industrial sustainability literature by applying a factory eco-efficiency modelling framework in a comparative study of the case company's cursory and detailed data. Facility, utility and manufacturing assets are modelled and analysed from logged data granularity factors.

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Peer-review under responsibility of the International Scientific Committee of the 13th Global Conference on Sustainable Manufacturing

Keywords: Factory; Eco-efficiency; Modelling; Data Granularity Framework; Data Composition; Simulation**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. Eco-efficiency could save more than one-fifth of projected manufacturing energy demand [2]. Alongside this material efficiency techniques that reduce the weight of inputs and losses in production can further this. For these reasons eco-efficiency is becoming an increasingly important organisational performance measure. Its indicators are regularly used alongside those of productivity, cost, quality, health and safety in operations and corporate social responsibility reporting.

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 modelled 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 UK furniture manufacturer's cursory and detailed resource and production data to model the eco-efficiency of their factory assets. Modelling results are discussed and conclusions on the framework's applicability are provided.

Nomenclature

Resources – Supply of materials, energy and water to factory
Data Granularity – Isolating resource data into distinct pieces
Asset Subdivision – Grouping of factory technical assets
Resource Magnitude – Data impact on performance indicators
Time-step – Frequency of data captured from asset logger
Performance Indicator – Measure of asset eco-efficiency

2. Literature Review

Eco-efficiency and modelling literature has been reviewed to derive the data granularity factors and performance indicators of the factory eco-efficiency modelling framework.

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 [6]. 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. It helps turn often-disparate raw data into useful information using eco-efficiency performance indicators. 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.

The need to be more eco-efficient provides the momentum organisations require for pursuing factory modelling [7]. However, beyond Lean there is little to support the analysis of resources across subdivisions [8]. Current modelling tools and techniques are informed by detailed knowledge of narrow functional boundaries [9]. 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 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. It has been designed to satisfy versatile user requirements, essential in developing representational factory models, with the ability to measure asset eco-efficiency [10].

2.2. Eco-efficiency Performance Indicators and Magnitude

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 [11] and environmental [12] benefits, implementation barriers and performance variation still continue [13]. Examination of the literature suggests a lack of systematic 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 [14]. 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 [15], 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, detailed in the framework section of this paper. 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.

The framework performance indicators include: power factor, water footprint, energy mix, material yield and energy per unit. Many performance indicators are applicable at multiple asset subdivisions. However some such as energy per unit are more applicable at manufacturing cells and single machine subdivisions. Whereas energy mix and power factor are more applicable at facilities and facility zones, when a number of different assets require eco-efficiency analysis. Framework performance indicators are linked with resources magnitudes across asset subdivisions. 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 framework 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 [16], utilities [17] and manufacturing [18] 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 [19], and increase the potential of sub-efficient

results [20]. Additionally, there is an ever-increasing number of modelling tools being used within these domains. Making selection of an appropriate tool more complicated when modelling multiple asset subdivisions with measurements logged at different time-steps [21].

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.

Modelling is a recognised means for providing the necessary dynamic environment to measure eco-efficiency within different time-steps. However, more guidance on the applicability of specific time-step granularities to consistently compose, model and indicate eco-efficiency is still required. The framework contributes to this area by consolidating 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 [22].

To develop knowledge in the area of data granularity the factory eco-efficiency modelling framework uses 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 can be used to measure and determine improvement opportunities at single or multiple time-step granularities, based on the application of best practices from specific industries [23]. Framework models incorporate the evaluation of energy distributions and material transformations [24] through the use of eco-efficiency indicators, which measure resource impact and improve performance of factory asset subdivisions [25].

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). The framework achieves this in a dynamic way through modelling. Framework models provide users with the ability to compose, model and analyse the eco-efficiency of their factory assets within and across available data granularities.

3.1. Framework Conceptual Model and Application Method

The conceptual model 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 the impact upon factory operations, making use of already existing resource data and promote framework modelling as a tool for continuous improvement [26]. Framework application shows results from cursory (per-quarter) and detailed (per-hour) measurements at facility zones, single zone utilities and manufacturing cell subdivisions. These subdivisions are comparatively 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 an earlier framework development and testing paper [27].

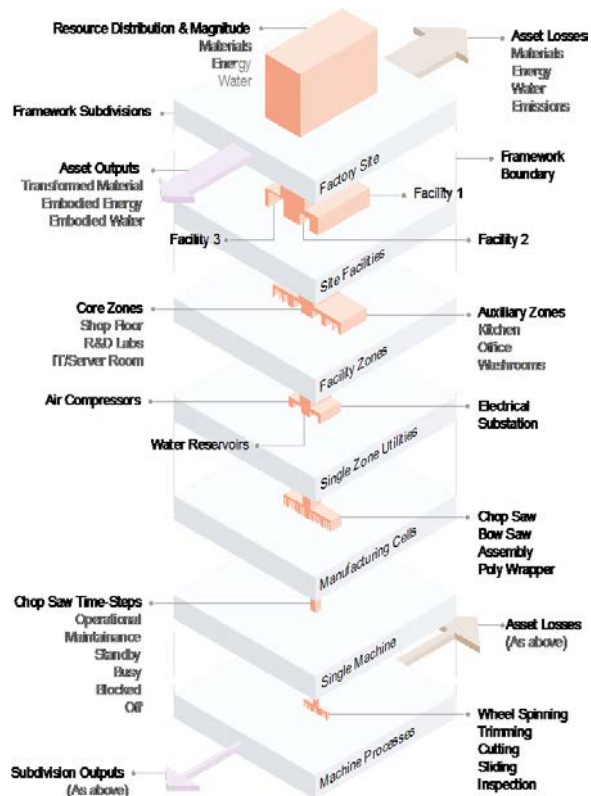


Figure 1. Framework schema integrates asset subdivision with resource time-step and magnitude *specified assets/resources shown are non-exhaustive and for demonstration purposes only

4. Framework Application

The framework was applied in a UK furniture manufacturer's factory. The case company is in the process of designing a new factory to help aid them in their growth as a designer-furniture manufacturer that is managing increasing client orders. Therefore an eco-efficiency analysis of current factory assets is desired to help indicate resource-saving opportunities, with a view for implementing improvements in the design of the new factory.

Facilities subdivision data, at per quarter time-steps for total electricity and production was captured. This data was composed in the framework and extrapolated at facility zones, utilities and manufacturing cell subdivisions based on original equipment manufacturer specifications, energy bills, and operational analysis undertaken with production experts.

A cursory model was produced to help verify assumptions made during the data composition process; the results from this showed that the majority of electrical energy consumption was from facility technical assets such as lighting and heating. However, the cursory model results also identified that some

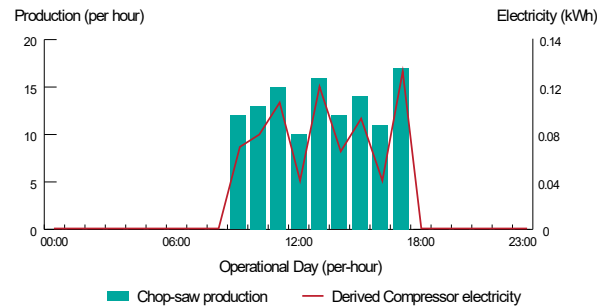


Figure 2. Manufacturing cell results extrapolated from cursory data

Results for the compressor and chop-saw assets were tenuous with cursory data alone. Therefore, detailed data composition and modelling of all electrical assets at per-hour time-steps was undertaken to confirm baseline energy consumption for these assets (figure 6).

To understand the impact that data granularity has on analysis of factory technical assets, a regression analysis on both data sets was undertaken at facility, utilities and manufacturing cell subdivisions. The comparative results are presented in the framework analysis to show correlation between cursory and detailed results, and their likely impact on decision making ability.

5. Framework Analysis

To help determine the accuracy of cursory model assumptions, data consistency, and model usefulness for understanding factory eco-efficiency, a regression of cursory vs. detailed data has been undertaken. This is presented at facilities (figure 3), utilities (figure 4) and manufacturing cell (figure 5) subdivisions.

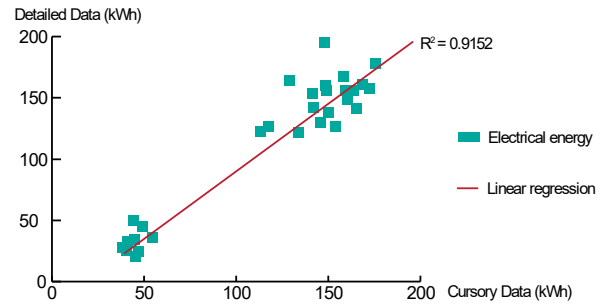


Figure 3. Facilities subdivision regression of cursory vs. detailed data

Facilities subdivision (figure 3) shows a correlation of 0.9 for cursory and detailed electrical energy data. One likely reason for the high correlation is the number of facility assets (e.g. lighting) that are in continuous use. This shows that cursory modelling and analysis at a facility level provides a strong indication of operational energy consumption.

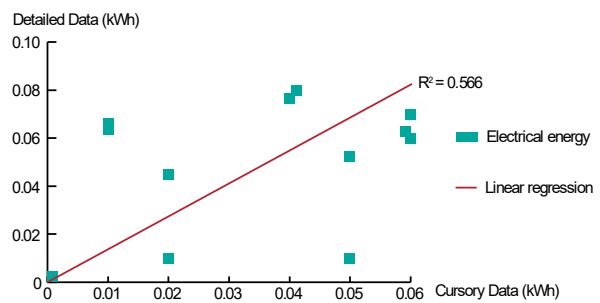


Figure 4. Utilities subdivision regression of cursory vs. detailed data

Utilities subdivision analysis for the compressor asset shows a 0.8 correlation. This indicates a relationship between the assumptions made in the cursory model, and detailed data. The operating variability of the asset makes a greater contribution to the final regression result, leading to a weaker correlation, suggesting a greater need for detailed modelling.

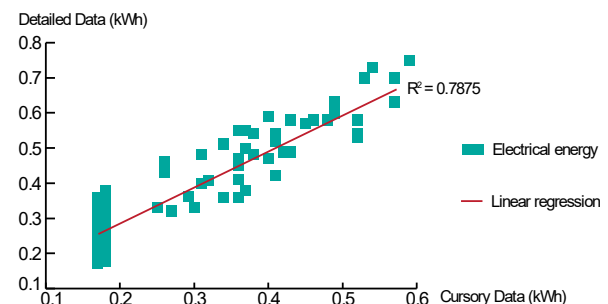


Figure 5. Manufacturing cell subdivision regression of cursory vs. detailed

A lower correlation of 0.6 for the chop-saw asset shows that variability between cursory and detailed data is higher at this level. Results indicate a need for detailed data-granularity modelling to provide consistent eco-efficiency performance.

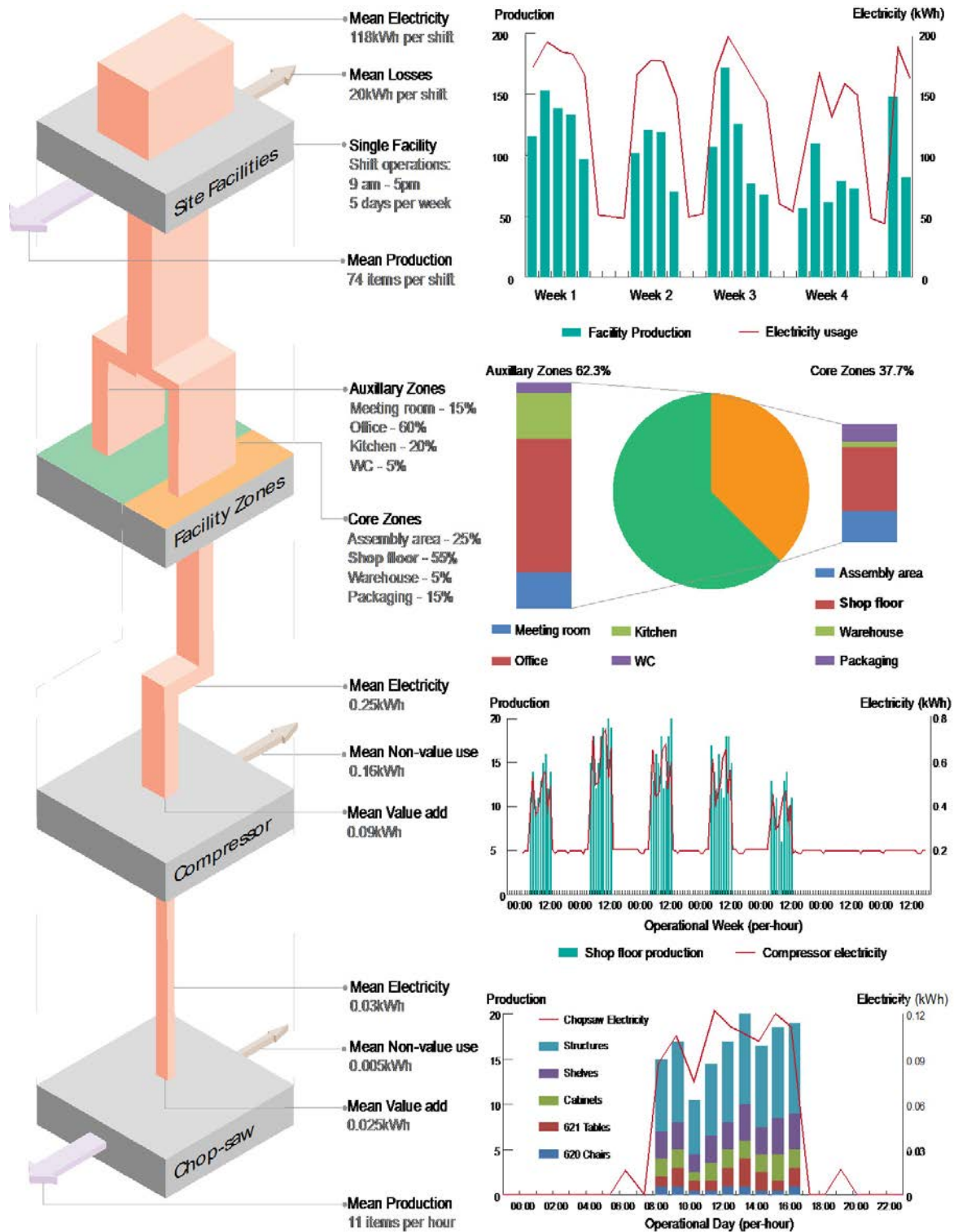


Figure 6. Detailed data modelling, indicators and results for facilities, facility zones, utilities and manufacturing cell subdivisions

6. Framework Applicability and Case Conclusions

The framework has been designed to further factory 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 to aid and inform decision making.

Data granularity factors for asset subdivision, time-step and resource magnitude are used to develop cursory and detailed models. The framework subdivisions presented in this case are facilities, facility zones, single zone utilities and manufacturing cells. This paper has shown that the framework is useful for developing both cursory and detailed models, which visualise asset eco-efficiency.

In the presented case the framework is used to understand the data granularity of resources within a furniture manufacture's factory. Initial modelling of cursory per-quarter data allowed for the extrapolation of electricity resource and material production data across facilities, facility zones, single zone utilities and manufacturing cell subdivisions. These results were verified with production experts, prior to modelling detailed per hour time-steps and magnitudes. Data was composed and modelled to determine the eco-efficiency baselines for the facility, compressor utility and chop-saw manufacturing cell. Regression analysis of cursory and detailed models for these assets showed the strongest correlation at facility level, indicating that for facility assets (e.g. lighting, heating, air conditioning) cursory data modelled with relevant assumptions can provide the indicators required for making informed decisions. However, at utilities and manufacturing cell subdivisions the correlation showed that detailed data composition and modelling are essential for making appropriate decisions and implementing technical interventions on highly variable operational assets.

This work contributes new knowledge to the area of industrial sustainability by showing how data granularity can be used to compose, model and indicate asset eco-efficiency using cursory and detailed data.

Acknowledgements

The authors would like to acknowledge the UK EPSRC Centre for Innovative Manufacturing in Industrial Sustainability (EP/I033351/1) for their support of this work. All data is provided in full in the framework application and analysis sections of this paper.

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2016-02-19

Elsevier

<http://dx.doi.org/10.1016/j.procir.2016.01.105>

Aanand Davé, Konstantinos Salonitis, Peter Ball, Mark Adams and David Morgan. Factory eco-efficiency modelling: framework application and analysis. Procedia CIRP, Volume 40, 2016, pp214-219. 13th Global Conference on Sustainable Manufacturing – Decoupling Growth from Resource Use