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Sustainability Cockpit: An integrated tool for continuous assessment and improvement of sustainability in manufacturing

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ABSTRACT

Sustainability assessment needs to be embedded into manufacturers' daily operations for continuous improvement. Existing factories, especially small and medium enterprises (SMEs), often lack infrastructure and capital to enable such regular assessment. An integrated tool has been developed based on a generic discrete event simulation (DES) factory model, which is linked to the company's resource planning system in order to not only assess the sustainability performance of each company's as-is operations, but also optimise their future performance. An Australian company was used as a case study to demonstrate the validity of the tool.

1. Introduction

Sustainability has become increasingly important for manufacturers, who have to make decisions under tremendous pressure to improve and maintain product quality and process performance while also considering environmental (e.g. carbon footprint of products) and social (e.g. safety regulations) challenges. Since the environmental impact of manufacturing activities is strongly dependent on the energy demand, improving energy efficiency has received initial attention within the context of sustainability [1]. Despite the expanding market of energy management tools for industries, in particular Small and Medium Enterprises (SMEs) are reluctant to implement those tools due to a lack of knowledge and experts to build up the necessary infrastructure (e.g. sensor) and to determine the return on investment [2]. Moreover, these commercialised tools are focused on energy, hence more or less on the one dimension of sustainability. As a result, contradictions between economic and environmental objectives are not addressed systematically.

To take up the needs of SMEs, instead of implementing a large-scale metering and monitoring system with high investment and operating costs, this paper proposes an integrated tool to estimate energy demand and resource consumptions via a factory simulation in combination with data linkage to an existing IT system (e.g. Enterprise Resource Planning, ERP). The tool includes a continuous (1) ex-post "explanation model" (as-is analysis) which allows a realistic process and product oriented allocation of energy demand and resource consumption; and, (2) ex-ante future "forecast model" (what-if analysis) to predict the effect of production strategies on both economic and environmental objectives as well as deriving optimal settings through the integration of simulation and optimisation.

Over the last decade, academics have developed different models with various focuses from the process level to the factory and supply chain level [3]. Simulation has proved to be able to effectively depict the complex energy and resource flows within a manufacturing system (e.g. [4–7]). However, those models were developed for infrequent use, the input of which was dependent on manual data acquisition rather than automatic data retrieval. Thus, existing models cannot be used in a straightforward manner for supporting daily decisions, and further development is required (see Section 2.3).

According to Kádár et al., there are number of challenges to adapt simulation models for short-term or even real-time decision support: (1) minimal maintenance efforts for data provision; (2) quick response time for simulation; and (3) ability to capture the dynamics over the time [8]. They also presented a system for a large scale manufacturing focusing on material flows and machine utilisation. However, energy flows and other environmental associated objectives were excluded in their approach. Furthermore, tactic planning requires the integrated function for multi-objective optimisation. Owing to the dynamic nature of energy and resource flows in manufacturing, the aforementioned challenges require the development of data sourcing strategies as discussed later in Section 2.2.

2. Methodology

The proposed tool has been developed under the framework of a collaborative industrial research project. The tool name,

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Sustainability Cockpit (SC), refers to a steering instrument in order to provide strategic decision support for the plant management in the form of sustainability-oriented objectives. A number of distinctive manufacturers were involved calling for a generic solution capable of dealing with scenarios ranging from typical batch production to a job-shop environment. They also have different IT infrastructures, thus adaptable data sourcing strategies need to be developed considering the availability and resolution of model input. This section presents key aspects of the SC, including the tool architecture, data sourcing strategies, the simulation model, and the optimisation module.

2.1. Architecture of Sustainability Cockpit

Fig. 1 presents the architecture of the proposed tool as a cyber physical system (CPS). In compliance with the idea of CPS, the tool consists of three main layers. The data layer (I) retrieves production data from the physical world on a regular basis and converts it into inputs for the cyber world (logic layer, II). Simulated scenarios are evaluated and visualised – either as as-is or what-if analyses – in the user-interface layer (III). Through user decision support improvement actions are initiated and conducted.

Data layer (I): This layer serves the functions for data sorting, data storage, and input data feeding. A dedicated Microsoft Access® database is developed for this tool which can be fed – depending on the factory's IT infrastructure – from multiple ports including ERP, MRP/MRP II, SCADA (Supervisory Control And Data Acquisition), metres and sensors. It is a supplementary tool rather than a replacement tool since a clear separation of databases will avoid interference and data loss. One-off data collection and metering activities are required to initially configure the tool. For instance, portable metering activities are required to obtain the energy profile of each process/process centre.

Logic layer (II): As the core part for the SC, the logic layer is based on a generic and parametric discrete event simulation (DES) model to characterise the energy and material flows within a manufacturing system (see Section 2.3). Model input is updated according to a user defined simulation period. The required input data is automatically sourced from the data layer. In addition, a multi-objective optimisation module is connected with the simulation model to derive optimal settings for future operation (see Section 2.4).

Graphical user interface (GUI) layer (III): This is the front end for user-input and results visualisation and is developed in Microsoft Excel®. Typical user input includes the simulation/assessment period, type of KPIs, optimisation objectives and their preferences, constraints for decision variables, etc. The GUI also allows user to configure a what-if scenario, e.g. alternative production plans for mid-term future. The GUI layer involves different methods for energy and time oriented analysis of process chains and factories, e.g. Sankey diagrams, different portfolios for decision support and energy value stream illustration.

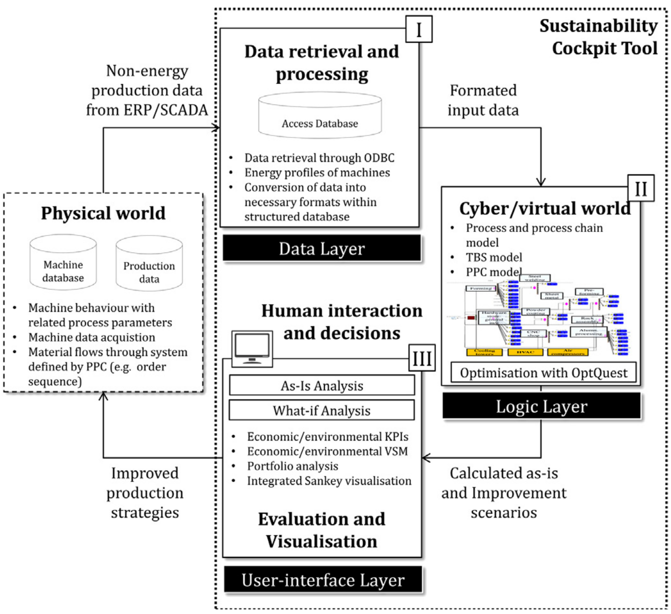

Fig. 1. System concept depicted as cyber physical system approach.

2.2. Data sourcing strategies

The prediction quality of the SC concept depends on (1) the data sourcing strategy and (2) the respective energy models for all involved technical equipment. Fig. 2 shows these influences in relation to a real measurement for a production order on a machine tool.

Owing to a continuous application of the simulation model, the data sourcing strategy needs to deal with the trade-off between modelling quality and maintenance effort. More direct input from actual measurements will decrease the dependency on assumptions and increase the accuracy of modelling results, but requires considerably more input data and longer response time.

The majority of the model inputs are predefined, such as the bill of materials (BOM) and the load profile of each process. This base data is augmented on a continuous basis with production data from company's IT system (e.g. master production plan, machine states). Depending on existing IT tools and the purpose of analyses, three data sourcing strategies (DSS) are defined. DSS1 as minimal option just provides start timestamps for orders. All other KPIs (e.g. lead time) are simulated based on process models and the defined idle time (e.g. for changeover). This data sourcing strategy is suitable for cases where only a basic ERP system is available such as the presented case in Section 3. Due to the simplification, only aggregated indicators are meaningful, such as total energy consumption over the period. DSS2 adds order end timestamps which brings predictions closer to real values. DSS3 involves start/finish times at each process which requires more sophisticated IT system (e.g. SCADA). Those timestamps can be used as event triggers, thus less assumptions have to be made. Accuracy of prediction significantly increases and instantaneous KPIs, such as peak power demand, can be derived accurately and traced at the time of occurrence.

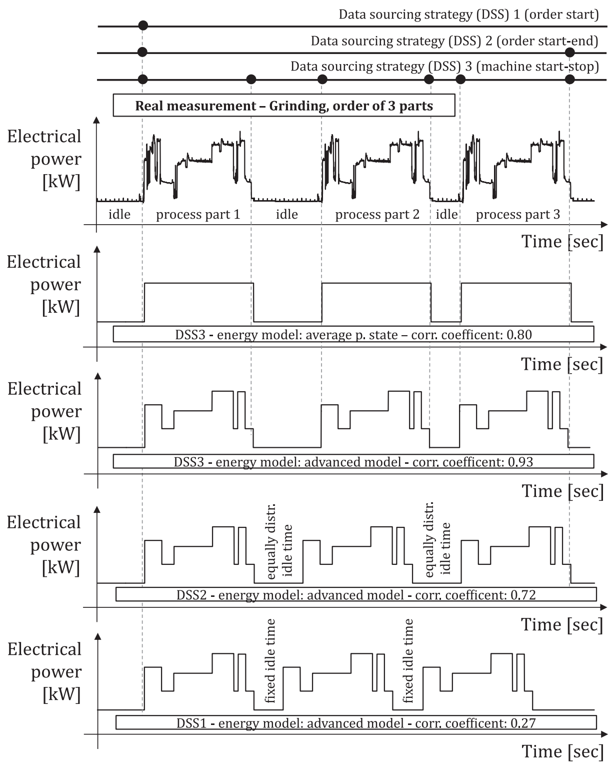

Fig. 2. Influence of data sourcing strategies and energy models.