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Enabling Effective Operational Decision Making on a Combined Heat and Power System using the 5C Architecture

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Abstract

The use of Cyber Physical Systems (CPS) to optimise industrial energy systems is an approach which has the potential to positively impact on manufacturing sector energy efficiency. The need to obtain data to facilitate the implementation of a CPS in an industrial energy system is however a complex task which is often implemented in a non-standardised way. The use of the 5C CPS architecture has the potential to standardise this approach. This paper describes a case study where data from a Combined Heat and Power (CHP) system located in a large manufacturing company was fused with grid electricity and gas models as well as a maintenance cost model using the 5C architecture with a view to making effective decisions on its cost efficient operation. A control change implemented based on the cognitive analysis enabled via the 5C architecture implementation has resulted in energy cost savings of over €7400 over a four-month period, with energy cost savings of over €150,000 projected once the 5C architecture is extended into the production environment.

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1. Introduction & Motivation

Industry 4.0 is a synonym for the transformation of today's factories to smart factories through the use of information technology within production environments [1],[2]. In an industry 4.0 enabled factory, field devices, machines and production systems seek to autonomously exchange information triggering optimisation actions [1].

Cyber Physical Systems (CPS) are defined as transformative technologies for managing interconnected systems between their physical assets and their computational capabilities [3]. Recent advances in sensor, data acquisition and network technology has facilitated a move by more factories to implement high tech methodologies towards production system optimisation [3] hence preparing the sector for the further proliferation of CPSs [4]. Flexibility in production processes can be achieved through IT integration between production systems, planning processes and supply chains [5]. The integration of CPSs into production systems would provide factories with the information to intelligently adjust production patterns [4] based on a fluid set of requirements.

Modern facilities are data-rich manufacturing environments that support the transmission, sharing and analysis of information across pervasive networks to produce manufacturing intelligence [6-8]. However, similar to other industries and domains, the current information systems that support business and manufacturing intelligence are being tasked with the responsibility of storing increasingly large data sets, as well as supporting the real-time processing of these large data sets using advanced analytics [9-14] when they were not designed to do so. Managing the vast quantities of data created by such connected systems, known as Big Data, requires careful consideration [4]. It is therefore critical to utilise a structured approach to acquiring, managing and analysing data in order to gain knowledge [4] for effective decision making. The 5C architecture provides a step by step approach to deploying CPS in the manufacturing sector [4].

This paper describes the fusion of data collected from a CHP system with grid electricity and gas models as well as a

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maintenance cost model using the 5C architecture. The goal of this research work was hence to identify the optimal usage profile of the CHP system to minimise its operating costs using both internal operational data and external cost and maintenance cost data. This work was seen as the first step in integrating the operation of the CHP system into the overall manufacturing planning process as once the generation efficiency of the CHP system was known, the use of waste heat in the factory could then be maximised. The contribution starts with Section 2 which provides a short review of related literature in this field with a view to positioning this research. Section 3 introduces a case study at a manufacturing company where the CHP system is described in operational detail. Section 4 then describes the application of the 5C architecture to this system to enable effective decision making with results and conclusions outlined in Section 5.

2. Review of Related Literature

The potential benefits of CPSs include improvements in operational efficiency, process innovation, and environmental impact [14,15]. As an example of a simple use case of this data added value, many companies do not know enough about where and how energy is consumed within their operations and hence do not have the knowledge to make decisions which would result in more efficient utilisation [5].

Relationships can be often be found between energy consumption and one or more suitable energy drivers in many production systems [16]. Based on this knowledge, Giacone et al [16] developed a structured framework to measure energy efficiency in industrial processes. This however was highly data dependent in order to populate the models developed to describe each process, data which proved difficult to obtain in many cases. In a similar vein, May et al [17] developed a method to identify the most applicable energy performance indicators (EnPIs) to allow the effective control of manufacturing equipment. As with previous studies however, the major limitation identified during this work was the availability of energy-related data to populate these advanced metrics

In a complimentary theme to this work, and based on the principle that load management of a manufacturing process can offer significant energy savings, Apostolos et al [18] found that tools and methods for the integration of energy efficiency into the manufacturing planning process in a systematic manner is becoming more important. Traditional closed loop control philosophies can result in less than optimal operation of manufacturing equipment assets which are not operated with their effects on ancillary systems taken into account. For example, industrial chilled water systems are often used to cool exhaust streams from high temperature processes when the use of the waste heat could be efficiently used in another part of the factory rather than being dissipated mechanically were the data there to support the holistic process control. However, as is now a common theme in all of these next generation optimisation systems/tools, a lack of available data has meant that data driven decision making is difficult

Leveraging data-driven analytics is an essential part of smart manufacturing. Indeed, many of the high-impact benefits of smart manufacturing are dependent on facilities being able to access, explore and analyse industrial data in a timely manner, while utilizing open standards and technologies. However, analytical capabilities can be impeded by time-consuming, complex and manual data integration. Weyer et al [1] discuss how the optimisation of the manufacturing sector is being impeded by the proliferation of proprietary and vendor specific standalone solutions in the field. The authors instead champion a more open, vendor agnostic approach and test this hypothesis by building a smart production line which is modular and scalable and full accessible in terms of future CPS integration.

Lee et al [3] presented a unified framework, the 5C architecture, for integrating CPS in manufacturing. The 5C architecture provides a step by step approach to deploying a CPS in the manufacturing sector [4]. At a high level, the 5C architecture [3] constitutes two key functional components: (1) real time data acquisition from the physical world and (2) intelligent data management and analytical decision making. In order to enact these two high level components, the 5C architecture proposes a sequential workflow which if followed will result in the construction of a CPS. Bagheri et al [4] implemented a short case study on the integration of the 5C architecture using three band saw machines in different geographical locations. Twenty different pieces of machine specific information were gathered from a PLC via the smart connection layer then transferred to the cloud for analysis in the cyber layer using an adaptive prognostic algorithm. This resulted in a machine health score which was then communicated to the user via a web based application with actions taken manually to optimise operations. D Wu et al [19] describe how CPS is expected to play a major role in the design and development of future Cloud-based design manufacturing (CBDM) systems. The authors describe how advances in CPS research can help integrate design and manufacturing related knowledge and principles as well as connect both cyber and physical components thus strengthening the case for the use of a standardised architecture such as the 5C CPS architecture to empower effective decision making in the manufacturing sector.

3. Method

In existing manufacturing companies, the enactment of the 5C architecture can prove difficult in practice as many manufacturing systems are not ready to manage big data due to a lack of smart analytic tools [8] and the presence of legacy equipment from where data is difficult to migrate to the conversion layer. This can be due to a number of reasons with for example, unconnected portions of network or unplanned and unstandardized growth resulting in non-standard communication protocols being utilised from proprietary vendors.

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