CORA Cork Open Research Archive
Cartlann Taighde Oscailte Chorcaí

Title	Enabling effective operational decision making on a Combined Heat and Power System using the 5C architecture
Authors	Bruton, Ken;Walsh, Brendan P.;Cusack, Donal Óg;O'Donovan, Peter;O'Sullivan, Dominic T. J.
Publication date	2016-11-02
Original Citation	Bruton, K., Walsh, B. P., Cusack, D. Ó., O'Donovan, P. and O'Sullivan, D. T. J. (2016) 'Enabling effective operational decision making on a Combined Heat and Power System Using the 5C architecture', Procedia CIRP, 55, pp. 296-301. doi: 10.1016/j.procir.2016.08.036
Type of publication	Article (peer-reviewed)
Link to publisher's version	10.1016/j.procir.2016.08.036
Rights	© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/). - http://creativecommons.org/licenses/by-nc-nd/4.0/
Download date	2026-11-01 01:42:14
Item downloaded from	https://hdl.handle.net/10468/3273

UCC
University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 55 (2016) 296 – 301

www.elsevier.com/locate/procedia

5th CIRP Global Web Conference Research and Innovation for Future Production

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

Ken Bruton[a,*], Brendan P. Walsh[a], Donal óg Cusack[a], Peter O'Donovan[a] & D. T. J. O'Sullivan[a]

[a] *Intelligent Efficiency Research Group (IERG), Department of Civil & Environmental Engineering, University College Cork, Ireland*

* Corresponding author. Tel.: +353 21 4902913 E-mail address: k.bruton@ucc.ie

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.

© 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production

Keywords: 5C Architecture; Cyber Physical Systems; Smart Manufacturing; Smart Grid; Integrated Energy Systems

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 manufacturing facilities are data-rich 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

2212-8271 © 2016 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).
Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production
doi:10.1016/j.procir.2016.08.036

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.

A demonstration facility was selected which is in the midst of undergoing a step change from conventional energy systems to that including a larger mix of renewable energy systems this being a common issue in large manufacturing [20,21] to test the implementation of the 5C architecture. This factory generates approximately 9 GWh of electrical energy from a 3MW wind turbine and approximately 3.5 GWh of gas generated electricity from 405kWe CHP system annually. With varying choices as to where to procure or generate electricity from, the existing automation control system is not equipped to make operating, energy and cost efficient choices as it was not designed for this purpose.

In order to bound the case study, the CHP system was selected as it is a somewhat complex system when compared to other utility systems whereby the use of the output streams impacted on its optimal operation, while the variable nature of the gas, electricity and maintenance costs meant that a static embedded closed loop control methodology not taking external factors such as cost of gas input to the system, cost of alternative electricity from the national grid or maintenance costs at time of operation into consideration was bound for sub optimal operation in terms of running costs.

The CHP system was found to be operating on a 24/7 basis and was capable of generating 405 kWe of electrical energy with 538kW of thermal energy as a by-product. An energy input of 1045 kW of gas was required to deliver these figures resulting in a design generation efficiency of 90.2%. On observation, the CHP generated between 399 and 404 kWe with heat supplied varying between 475 and 510kW. On spot check analysis however, as little as 250kW of this heat was utilised in the factory with the remainder dumped via blast coolers. This constituted a generation efficiency of just 84% and a useful operating efficiency of just 62.4%.

In order to inform a more strategic data driven decision process to minimise the cost per kWh electricity generated by the CHP system, the 5C architecture was proposed for implementation to capture operational data to allow analysis to inform decision making. This was seen as the first step in maximising the operational performance of the system. The next step, which is discussed in Section 5, will be to maximise the use of waste heat generated through the integration of heat loads from the factory floor, thus maximising generation efficiency and elongating the operational hours where the cost to generate electricity from the CHP is less than that which could be procured from the national grid.

4. Implementation of 5C Architecture

4.1. Smart Connection Level

The CHP (Sokratherm GG 402) system was surveyed in August 2015 with a view to ascertaining its current operation. It was controlled by a Programmable Logic Controller (PLC) via an embedded closed loop control algorithm based on maximising the electrical output with little heed to the heat utilised. It communicated with a Building Management System (BMS) via Modbus connection to a Cylon© BMS. The BMS could enact time-schedule control, but the PLC controlled all other key operational parameters.

On inspection of the BMS, it was found that a Comma Separated Value (CSV) based data archive was maintained for each point routed through the system once it was set to log daily at 5am (Table 1). This system recorded one CSV file for each data point, with one new line of data appended each day at the set logging timestamp. This line of data constituted 1024 data values with a value recorded for each 900 second (or 15 minute) interval. This constituted approximately 10.67 days of logged data (96 values per day).

Table 1: Format of CHP Power Generation point recorded in Cylon generated CSV log file

UC32netK/Web/MOD-002-UC3224	*CHP Power Generation*	*900*	*kWh*	
42392.60417	1024	401	401	400

Electricity and gas costs were available via a MS Excel based spreadsheet which was maintained by the facilities department within the manufacturing company. This spreadsheet detailed the unit cost and transmission costs per kWh of electricity and gas based on the time of day in which they were consumed. This spreadsheet was largely static but was recently updated due to a new procurement contract. It typically updated annually. Maintenance costs were obtained from a third party contract on a per kWh generated schedule. These were taken as a fixed cost per kWh for analysis purposes with no time of day impact.

4.2. Data to Information Conversion

The data ingestion process was implemented as a single-thread C# .NET application, which utilized AWS SDK for .NET to facilitate communication between the factory and cloud infrastructures. The data ingestion application was deployed on the BMS PC in the facility, with a scheduled task set to trigger its execution at 09:00 each day. During the exploration phase it was found that there were a number of issues that caused difficulty in obtaining the BMS data and preparing and transferring it to a remote location for analysis. Firstly, the four key points recorded for the CHP system as detailed in Table 2 were of different measurement types. The CHP Power, Heat Generation and Heat Dump values were all taken as instantaneous values while the Gas Consumption was recorded as a totalised cumulative value each 15 minutes. The units also needed to be taken into account as they would need to be normalised for further analysis.

Table 2: CHP Points logged via Cylon BMS

CHP Point	Filename	Unit	Meter Type
CHP Power Generation	D0010208	kWh	Instantaneous
CHP Heat Generation	D0010209	kWh	Instantaneous
CHP Heat Dump	D0010210	kWh	Instantaneous
CHP Gas Consumption	D0010211	M^3	15 minute cumulative

Secondly, due to the poor interoperability and integration methods exposed by most BMS software, extracting and integrating BMS data can result in many data anomalies, including missing or null values, irregular timestamps (e.g. dd/mm/yyyy hh:mm compared to yyyy-mm-dd hh:mm), differing numerical representations (e.g. percentage measurements can be represented as an integer or as a floating point number) and spurious outliers in the data that need to be corrected or removed prior to processing, storage and further analysis. The workflow described in Table 3 addressed anomalies in the ingested data by transforming the proprietary format to a basic time-series. The basic time-series leads to data redundancy being removed with measurements consolidated: each row now representing a single observation (i.e. point-in-time) and each column representing a single variable (i.e. timestamp and value).

Table 3 CHP data workflow modules

Type	Name	Description
Parser	*cylon-log (stage 1)*	Transforms Cylon log files to a time-series format with timestamp and value.
Mapper	*chp-points (stage 2)*	Renames the auto-generated filenames using a convention for CHP instrumentation.
Aggregator	*time-series*	Merges log files for CHP instrumentation and writes contents to a single file.

There were no such issues with the electricity, gas and maintenance costs as the excel spreadsheets were organised in such a manner that they were easily transformed and archived for analysis.

4.3. Cyber Level

A Matlab model (Figure 1) was built (using Equations 1 & 2) to determine the cost per unit of electricity generated by the CHP system when compared to the cost per unit of electricity purchased from the national grid taking maintenance costs into account.

Equation 1 : CHP Fuel Conversion Efficiency

$$\boldsymbol{\eta_{FE}} = \frac{\mathbf{E_E}}{\mathbf{E_G} - \frac{\mathbf{Q}}{\boldsymbol{\alpha}}} \times \mathbf{100} \quad (1)$$

Equation 2: Cost per unit of electricity generated

$$\mathbf{C_E} = \frac{\mathbf{E_G} - \frac{\mathbf{Q}}{\boldsymbol{\alpha}}}{\mathbf{E_E}} \quad (2)$$

Where:

η_{FE} = CHP Fuel Conversion Efficiency (%)
C_E = Cost per unit of electricity generated by CHP (€)
E_E = Total electric power output by CHP (kWh)
E_G = Total energy entering as fuel (Gas) Input (kWh)
Q = Useful heat generated (kWh)
α = Efficiency of technology that would otherwise be utilised to produce thermal energy (i.e. gas boiler efficiency)

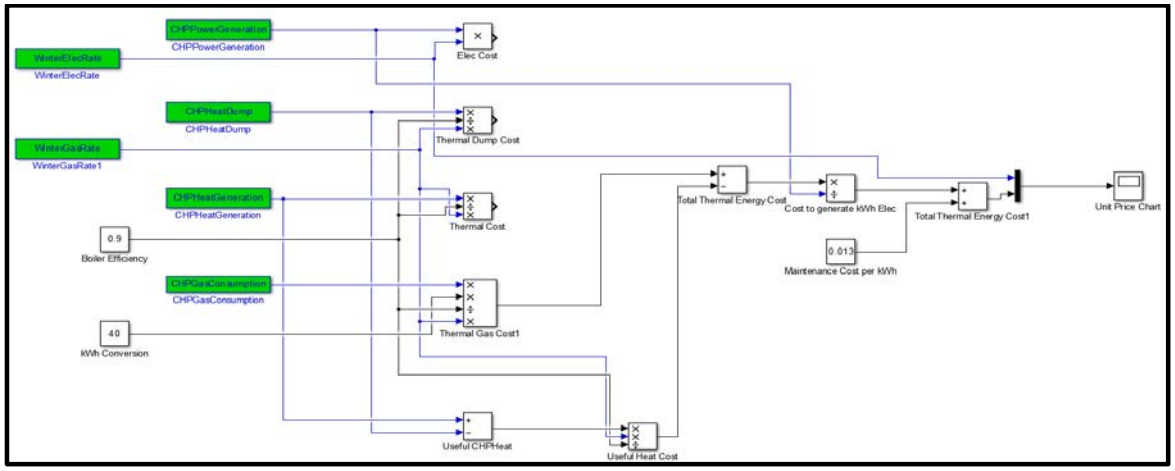


Figure 1: Matlab Model utilised to calculate the unit price of CHP generated electricity

Data for each of the key variables was fed into the Matlab model from the processed logged data and combined with the electrical and natural gas data based on time of day and the cost per kWh to maintain the CHP system. By merging the machine level PLC data with the grid price and maintenance models in this layer and exposing one value, the cost to generate electricity at any given time, the facilities engineers on the case study site could, for the first time, make knowledge based decisions as to when the operate the CHP system effectively. This data also facilitates the next step to the optimisation of this assets operation, that being to increase the use of its waste heat within the production environment, thus minimising the cost to generate each kWh of electricity and eventually extending its hours of operation.

The next phase of this project includes taking data from a cleaning process within the factory where de-ionised water is

currently heated electrically at end use point and evaluating the potential to utilise CHP waste heat to replace or supplement this process. This has the potential to be a major cost saving project for the case study manufacturing site with savings in excess of €150,000 per annum potentially possible through the elimination of the electrical heating elements, the removal of current cooling on the waste heat stream from the CHP system and the elongation of operational hours of the CHP thus reducing electrical consumption costs. The 5C architecture has allowed the merging of disparate data sources within the factory to be done in a standardised and repeatable manner. It has also exposed the mechanism by which a CPS can be built using a bottom up approach. The CHP data was initially analysed in the Cyber layer in isolation, then merged with maintenance and grid cost models and eventually will be merged with factory level production data.

4.4. Cognition Level

The Simulink output from the Matlab model was utilised to aid the facilities engineers in making effective decisions as to when to operate the CHP system to minimise its operational cost. Figure 2 details the graphical (Simulink) results of this analysis showing that the CHP system was generating electricity at a unit cost greater than that which could be procured from the national grid for over 37% of its operational time. There were a number of reasons for this operational deficiency. The cost of grid electricity had reduced since the CHP system was installed and this control put in place. This grid electricity price drop coupled with a lack of a similar price reduction for gas had resulted in what is known as a 'spark price' (the gap between the electrical and gas prices) reduction. Another contributing factor is the non-optimal use of the heat generated by the CHP system, with approximately only 50% of this being utilised with the remainder being dumped via cooling towers. The latter pointing to the potential to extend the analysis carried out in the cyber layer to the production environment as previously described in section 4.3.

4.5. Configuration Level

The decision making surrounding the operation of the CHP system is now being done using the output from the Matlab model via Simulink. Figure 3 details the result of the control strategy change implemented based on the analysis undertaken in the Cyber layer with the CHP now only operational during the more financially beneficial daytime period. This decision was informed by the Matlab model analysis made possible by the implementation of the first three steps of the 5C architecture. Therefore further research is required in order to automate this decision loop via the effective implementation of the fifth step of the 5C architecture.

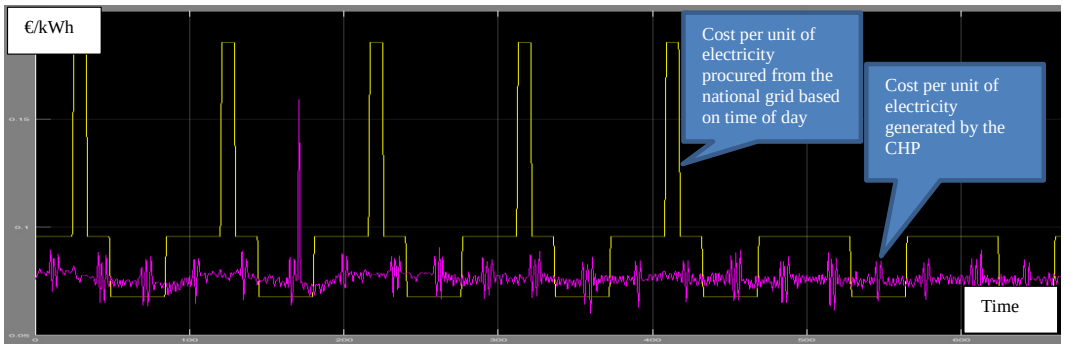


Figure 2: Comparison of Grid electricity unit price versus CHP generated electricity unit price

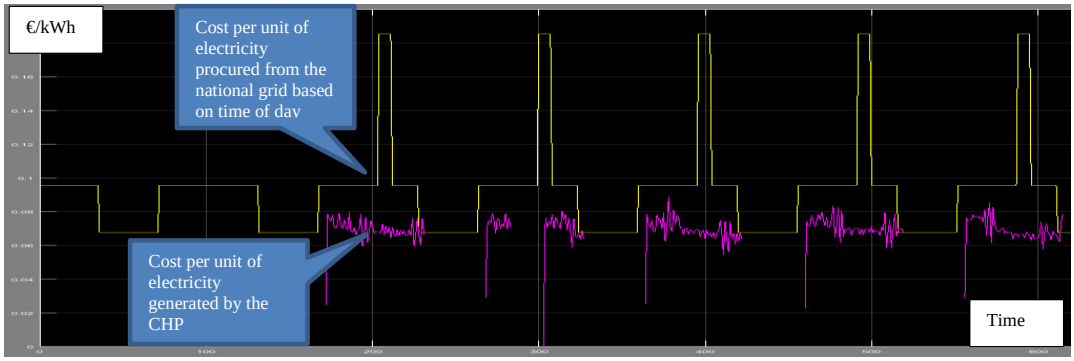


Figure 3: Altered operational control strategy

5. Results & Conclusions

The 5C architecture has facilitated effective decision making on the cost efficient operation of the CHP system. The unit price to generate electricity using the CHP system was determined to be less than the grid price during the winter (November – February) weekday period only. Based on the projected unit price of daytime (08:00 – 23:00) and night-time (23:00 – 08:00) electricity in the coming summer period, this finding will hold for this period also. The control change enacted on the CHP system for the previous winter period has resulted in financial savings of €7400 being delivered based on a business as usual scenario. If this control change was maintained for the duration of the year, savings of over €20000 would be achieved.

The current operation of the CHP system at just 62.4% generation efficiency is not sustainable in the long term as the system is not being optimally utilised. It is critical to utilise the waste heat generated from a CHP system during the generation of electricity in order to minimise the cost to generate electricity from the CHP. It is therefore essential to improve the utilisation of the useful heat generated by the CHP system in order to raise this generation efficiency and in doing so reduce the cost to generate electricity from the unit. By doing this, the pinch point of 6.77c/kWh will be reached when approximate 65% of the waste heat is being usefully consumed and the operational timeframe of the unit can be extended.

Initial analysis has found a matching electrically driven heat sink on a cleaning process present in the factory which potentially could result in over 80% of the waste heat from the CHP system being utilised. This would also serve to reduce the load on the blast coolers which currently operate to cool the waste heat ejected from the system. In order to do this however, the operation of the cleaning process would need to be analysed in conjunction with that of the CHP system, thus bringing the manufacturing floor into scope and thus widening this research work in the Cyber Level of the 5 C architecture.

References

[1] Weyer S, Schmitt M, Ohmer M, Gorecky D. Towards Industry 4.0 - Standardization as the crucial challenge for highly modular, multi-vendor production systems. IFAC-PapersOnLine 2015;48:579–84. doi:10.1016/j.ifacol.2015.06.143.

[2] Kolberg D, Zühlke D. Lean Automation enabled by Industry 4.0 Technologies. IFAC-PapersOnLine 2015;48:1870–5. doi:10.1016/j.ifacol.2015.06.359.

[3] Lee J, Bagheri B, Kao H-A. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manuf Lett 2015;3:18–23. doi:10.1016/j.mfglet.2014.12.001.

[4] Bagheri B, Yang S, Kao H-A, Lee J. Cyber-physical Systems Architecture for Self-Aware Machines in Industry 4.0 Environment. IFAC-PapersOnLine 2015;48:1622–7. doi:10.1016/j.ifacol.2015.06.318.

[5] Faller C, Feldmüller D. Industry 4.0 Learning Factory for regional SMEs. Procedia CIRP 2015;32:88–91. doi:10.1016/j.procir.2015.02.117.

[6] Davis J, Edgar T, Porter J, Bernaden J, Sarli M. Smart manufacturing, manufacturing intelligence and demand-dynamic performance. Comput Chem Eng 2012;47:145–56. doi:10.1016/j.compchemeng.2012.06.037.

[7] Chand S, Davis J. What is Smart Manufacturing ? Time Mag 2010.

[8] Lee J, Kao HA, Yang S. Service innovation and smart analytics for Industry 4.0 and big data environment. Procedia CIRP 2014;16:3–8. doi:10.1016/j.procir.2014.02.001.

[9] Lee J, Lapira E, Bagheri B, Kao H. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf Lett 2013;1:38–41. doi:10.1016/j.mfglet.2013.09.005.

[10] Kumar P, Dhruv B, Rawat S, Rathore VS. Present and future access methodologies of big data. Int J Adv Res Sci Eng 2014;8354:541–7.

[11] McKinsey. Big data : The next frontier for innovation , competition , and productivity. 2011.

[12] Philip Chen CL, Zhang C-Y. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. Inf Sci (Ny) 2014;275:314–47. doi:10.1016/j.ins.2014.01.015.

[13] Vera-baquero A, Colomo-palacios R, Molloy O. Towards a process to guide Big Data based Decision Support Systems for Business Processes. Conf. Enterp. Inf. Syst. Towar., vol. 00, 2014.

[14] Fosso Wamba S, Akter S, Edwards A, Chopin G, Gnanzou D. How “big data” can make big impact: Findings from a systematic review and a longitudinal case study. Int J Prod Econ 2015:1–13. doi:10.1016/j.ijpe.2014.12.031.

[15] Hazen BT, Boone C a., Ezell JD, Jones-Farmer LA. Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. Int J Prod Econ 2014;154:72–80. doi:10.1016/j.ijpe.2014.04.018.

[16] Giacone E, Mancò S. Energy efficiency measurement in industrial processes. Energy 2012;38:331–45. doi:10.1016/j.energy.2011.11.054.

[17] May G, Barletta I, Stahl B, Taisch M. Energy management in production: A novel method to develop key performance indicators for improving energy efficiency. Appl Energy 2015;149:46–61. doi:10.1016/j.apenergy.2015.03.065.

[18] Fysikopoulos A, Papacharalampopoulos A, Pastras G, Stavropoulos P, Chryssolouris G. Energy Efficiency of Manufacturing Processes: A Critical Review. Procedia CIRP 2013;7:628–33. doi:10.1016/j.procir.2013.06.044.

[19] Wu D, Rosen DW, Wang L, Schaefer D. Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. Comput Des 2015;59:1–14. doi:10.1016/j.cad.2014.07.006.

[20] Johnson J&. johnson & johnson commits to new energy and climate goals 2016. http://www.blogjnj.com/2015/09/johnson-johnson-commits-to-new-energy-and-climate-goals (accessed March 10, 2016).

[21] GSK. Heeding the warning: big/small changes to get to carbon neutral 2016. http://us.gsk.com/en-us/our-stories/our-planet/heeding-the-warning-bigsmall-changes-to-get-to-carbon-neutral (accessed March 10, 2016).