11th Brazilian Congress on Manufacturing Engineering
May 24th-26th, 2020, Curitiba, PR, Brazil

OPTIMIZATION OF ENERGY EFFICIENCY IN SMART MANUFACTURING THROUGH THE APPLICATION OF CYBER-PHYSICAL SYSTEMS AND INDUSTRY 4.0 TECHNOLOGIES - A SYSTEMATIC REVIEW

Matsunaga, Fernando
Federal University of Parana (UFPR), Curitiba - PR 81530-000
Brazil (Tel: +55 (41) 99650-1919; e-mail: fernando.matsunaga@ufpr.br).

Valle, Pablo
Federal University of Parana (UFPR), Curitiba - PR 81530-000
Brazil (Tel: +55 (41) 3361-3207; e-mail: pablo.valle@ufpr.br).

Deschamps, Fernando
Federal University of Parana (UFPR), Curitiba - PR 81530-000
Brazil (Tel: +55 (41) 99915-2600; e-mail: fernando.deschamps@ufpr.br).

Abstract. *Energy efficiency plays a key role in the sustainability and economic competitiveness of the industrial sector, being an essential strategy in the long-term for business and society purposes. This paper serves as a systematic review to identify how smart manufacturing and cyber-physical systems, in the context of industry 4.0, are leveraging results in manufacturing energy efficiency and as opportunities identification in the topic. Among all technologies investigated, a gap was identified in the literature with researches that proposes the integrated usage of cyber-physical systems and digital twins as a relevant tool to boost results in energy efficiency in smart manufacturing context.*

Keywords: *the fourth industrial revolution; energy efficiency; cyber physical systems; CPS; digital twin; smart manufacturing; sustainable manufacturing;*

1. INTRODUCTION

Industrial activity has a considerable share in the total worldwide energy consumption mix, in which industries can account up to 41,9% of total electricity consumption (Ranganadham, 2018). This high-energy consumption factor of the industrial sector, leads to great opportunities in energy efficiency, not only for cost reduction purposes, but also to lower the impact of industrial activity in achieving the UN Sustainable Development Goals (SDGs) by 2030. In that matter, industry 4.0 plays a key role in achieving those targets (Nagasawa et al., 2017), enabling the industrial sector to lower its CO_2 footprint along with the competitiveness improvement that results from measures in energy efficiency activities.

This paper intends to evaluate the application of Industry 4.0 technologies to improve energy efficiency in manufacturing in the context of smart-manufacturing, cyber-physical systems and other emerging technologies that can significantly enhance the possibilities in this field. As main objectives, this paper intends to answer three research questions:

Q1: Which methodologies and approaches are most commonly applied in energy efficiency in smart manufacturing?

Q2: Which smart manufacturing technologies are enhancing significantly the results in energy efficiency?

Q3: What are the use cases of Cyber-physical system technologies in improving energy efficiency in manufacturing?

In order to achieve these objectives, section 2 presents a systematic literature review and section 3 describes the promising technologies, methodologies and applications for the improvement of energy efficiency in manufacturing.

2. SYSTEMATIC LITERATURE REVIEW

2.1 Data Collection and Filtering

For the state-of-the-art analysis a systematic literature review (SLR) was conducted through the application of the Proknow-C method (Ensslin et al., 2010). The application of a SLR enabled a concrete approach to establish a relevant publication basis on the research context, including the application of technologies, terminologies and trends in energy efficiency in manufacturing areas. Three main research focuses and respective search terms (Table 1) were defined to help answering questions 1 to 3 in section 1.

Table 1. Research focuses and search terms [author]

Energy Efficiency	Manufacturing Simulation	Smart Manufacturing
"energy consumption models"	"cyber physical system"	"industry 4.0"
"energy efficiency"	"cyber-physical integration"	"machining process"
"energy efficient manufacturing"	"digital factory (df)"	"manufacturing"
"energy management"	"digital twin"	"production machines"
"energy monitoring	"digital twin shop-floor (dts)"	"production management and control"
"energy saving"	"manufacturing cyber-physical system"	"smart factory"
"equipment energy consumption management (eecm)"	"virtual shop-floor"	"smart manufacturing"
"industrial energy consumption"	"shop-floor digital twin data (sdtd)"	"sustainable manufacturing"
"specific energy consumption"		"sustainability"

With the defined research focuses and search terms, a research string was created with AND connector for research focus and OR for search terms and inputted in the databases Scopus and Web of Science. This research string achieved a satisfactory repertory (127), showing a comprehensible and manageable number of publications. First attempts using energy efficiency and smart manufacturing as research focuses resulted in more than 15.000 publications.

After this initial selection of portfolio, the 127 papers were filtered removing conference publications and considering only papers in English and merged with pre-selected articles related to the research topics. Applying the filters and also removing duplicates between the databases, the total amount of publications left for analysis were 117, in which were according to the Proknow-C method filtered and categorized as shown in Figure 1.

The final literature repository was then defined in the 56 remaining papers which had their full content analyzed, with end result of 41 publications that were aligned with the objectives of this papers.

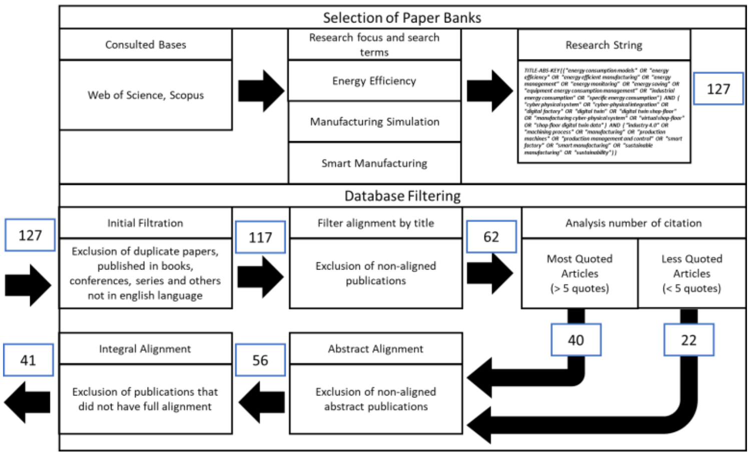

Figure 1. Filtering steps and final repository with 41 papers. [author]

3. ENERGY IMPROVEMENT IN MANUFACTURING

As presented in section 2.1 energy efficiency in manufacturing has been a very relevant topic throughout the last decades achieving the number of thousands of publications in that regard. In the context of manufacturing industries, many distinct methodologies for energy efficiency approaches, technologies and measures have been broadly discussed in the literature and those will be summarized in this specific section of the paper.

3.1 Methods and Frameworks

The methodological approaches, frameworks and models of energy consumption in manufacturing serve as an important base for the identification, management and implementation of energy efficiency measures in manufacturing. The results achieved by a methodological approach can be further potentialized with the applications of smart manufacturing technologies (Zhou et al., 2016). In this section a small summary of the methodologies found in the literature are briefly reviewed.

3.1.1 Equipment Energy Consumption Management (EECM) and Machine Specific Energy Consumption (SEC)

Equipment Energy Consumption Management (EECM) and Machine Specific Energy Consumption (SEC) are both methods to improve energy consumption optimization of machines and equipment through optimization of processes characteristics, such as machining parameters, scheduling sequences and tool parameters (Zhang, Zuo, & Tao, 2018). Energy consumption in the machining stages are divided in start-up period, idle periods and cutting periods. Relevant aspects that should be evaluated in a SEC analysis is the design and optimization for energy-efficient, scheduling management and the energy efficiency and environmental impact assessment (Y Feng, Wang, Gao, Cheng, & Tan, 2018). In Figure 2 we have a typical milling machining process curve. Remembering that the EC is calculated by the multiplication of the time axis with the power demand.

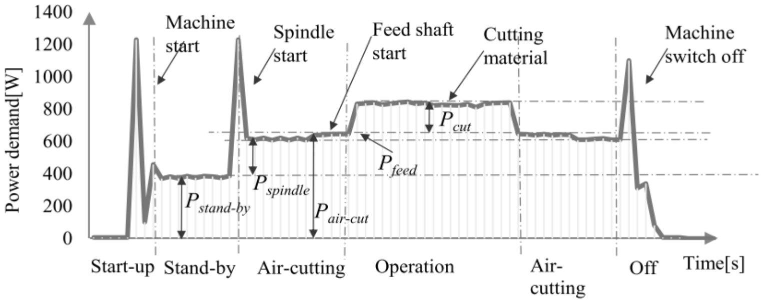

Figure 2. A schematic diagram of power profile of the milling process (Zhou et al., 2016)

For the analysis of SEC many further models can be used such as model based in linear type of cutting energy consumption, on material removal rate (MMR), main cutting parameters, detailed parameter type of cutting correlation models, metal deformation theory, amount of tool wear, on cutting force, explicit analytical model, neural network black-box model, process-oriented machining. More details on the models can be found in specific machine tool energy efficiency model papers (Zhou et al., 2016).

3.1.2 Energy-related key performance indicators (e-KPIs)

For the improvement of energy efficiency in manufacturing processes, it is also relevant to have key performance indicators to serve as potential energy efficiency measure identification tool, as whereas a tracking of performance improvement tool in the shop floor. Current indicators such as OEE (Overall Equipment Effectiveness) are time based indicators that are not best fit for energy efficiency purposes or also aggregate energy consumption indicators such as kWh/month or kWh/parts that lacks cause-effect relationship, proving to be inefficient for energy efficiency potential identification. (May, Barletta, Stahl, & Taisch, 2015). May et al. propose a seven steps approach for e-KPI definition and management.

3.1.3 ISO 50001

ISO (international standardization organization) has established the standard ISO 50001 to specify requirements for establishing, implementing, maintaining and improving an energy management system, whose purpose is to enable an organization to follow a systematic approach in achieving continual improvement of energy performance, including energy efficiency, energy usage and consumption. It is also based on the common elements of ISO management system standards, ensuring a high level of compatibility notably with ISO 9001 and ISO 14001 (International Organization for Standardization, 2018).

3.1.4 Life Cycle Analysis and Life cycle energy analysis (LCA and LCEA)

Life-cycle assessment (LCA, also known as life-cycle analysis, ecobalance and cradle-to-grave analysis) is a technique to assess environmental impacts associated with all the stages of a product's life from raw material extraction through materials processing, manufacture, distribution, use, repair and maintenance, and disposal or recycling. Designers use this process to help critique their product (US Environmental Protection Agency., 2010).

Due to the information intensive nature of LCA and the lack of accurate data related to energy demand across a product life cycle (in particular during the manufacturing phase), significant assumptions and simplifications are often made. This has motivated numerous research programs to investigate energy consumption within a manufacturing facility so as to gain a better understanding of the energy usage and breakdown (Seow & Rahimifard, 2011).

3.1.5 Embodied Product Energy (EPE) Framework

Embodied Product Energy (EPE) framework brings more detail to the LCA approach, with the aim of representing the amount of energy attributed to the manufacture of a unit product. For that reason, indirect and direct energy are accounted being defined in this methodology as theoretical energy (TE) (minimum of energy required for direct manufacturing such as melting or machining) and auxiliary energy (AE) (all the indirect energy required for the production of the items) (Seow & Rahimifard, 2011). Further steps of the framework are the modelling embodied product energy and energy simulation as depicted in Figure 3.

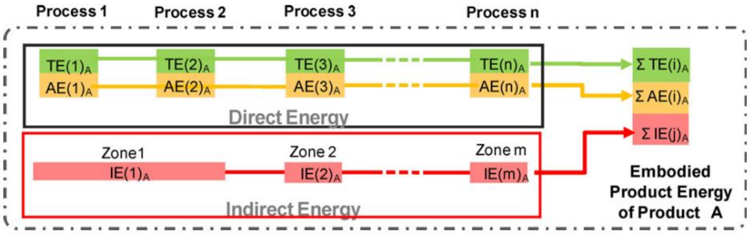

Figure 3. Framework for modelling embodied product energy (Seow & Rahimifard, 2011)

3.1.6 Material and Energy Flows

Material, energy and information flows are relevant tools for process understanding and management. Therefore, this framework of energy and material flow are usually applied together with Value Stream Mapping techniques in order to understand in a comprehensible approach how information, material, people and machinery correlate to each other in production environment. In Figure 4 we have an example of an energy, material and information flow applied for energy efficiency (Ma, Zhang, Lv, Yang, & Wu, 2019).

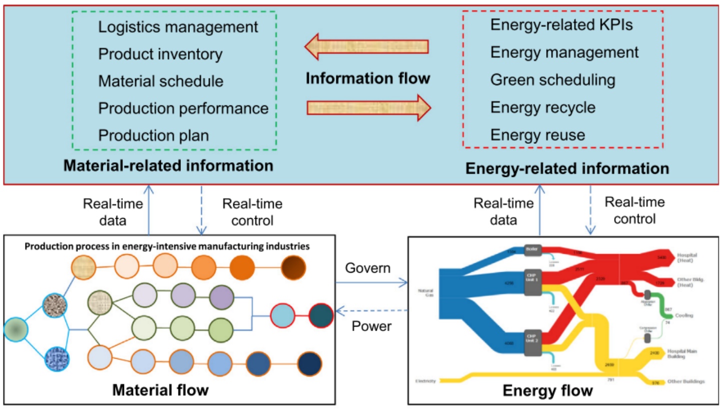

Figure 4. Closed-loop structure of energy flow, material flow and information flow. (Ma et al., 2019)

3.1.7 Remaining energy-efficient lifetime (REEL)

REEL is defined as the remaining energy efficient lifetime of a system, in which an equipment or system reaches a non-energy efficient threshold that alerts decision makers of the necessity for the replacement of the asset or renewal. With the development of new smart manufacturing technologies, the prognostics to determine the REEL have become much more precise and realistic through the monitoring and data acquisition, the modelling of energy efficiency and finally the prediction of the REEL. (Hoang, Do, & Iung, 2016).

3.1.8 Conservation Supply Curve (CSC) and marginal Cost of Conserved Energy (CCE)

In general, the CSC (Conservation Supply Curve) assesses the cost effectiveness and the technical chances for energy efficiency. The energy conservation potential is shown as a function of the marginal CCE (Cost of Conserved Energy) and provides a clear visualization of energy efficiency. CCE allow for making explicit the impact of maintenance and productivity optimization on energy saving. The application of this model is described in details in distinct literature references (Demichela, Baldissone, & Darabnia, 2018).

3.1.9 MAESTRI Total Efficiency Framework (MTEF)

The MTEF represents a flexible and scalable platform, which provides an effective management system that aims to advance the sustainability of manufacturing and process industries. It combines four pillars (Technical/Technological Gaps, Management Gap and Organizational Gaps) in one holistic platform, which enables an overall efficiency performance assessment from environmental (including resource and energy efficiency), value and cost perspectives. MTEF encompasses Environmental Performance Evaluation with Environmental Influence and Cost/Value assessment models through a life cycle perspective. The aim is to support the decision-making process, by clearly assessing resource and energy usage (valuable / wasteful) of all process elementary flows, and the eco-efficiency performance. It is based in a lean approach, with decision support via value-adding optimization that is also foreseen among the integration of the modules (Paper, Ferrera, Rossini, & Evans, 2017).

3.1.10 Empirical Characterization and Industrial surveys for exergy analysis

Unlike analytical approaches, empirical modelling uses observations and statistical analysis to characterize the relationship between cause (variables) and effect (responses). The derived relationship can be potentially used to estimate the theoretical limit. It is often used in conjunction with Design of Experiments (DOE) and has been successfully adapted to characterize the energy efficiency of unit processes. However, it is not directly applicable at a factory level. The reasons are twofold: one is that there are numerous potential factors and unknown variables; the other one is that it is impossible and costly to run scheduled experiments at the factory level. (Mahamud, Li, & Kara, 2017).

3.1.11 Energy Consumption Monitoring, Analysis and Optimization with application of DTS (Digital Twin Shop-floor)

With the application of the DTS (Digital Twin Shop-floor) environment, the evaluation of energy consumption (EC) of a determined equipment becomes much more accurate, following the EC monitoring, analysis and optimization. Since data from both the physical and virtual equipment are available, the equipment energy consumption condition management (EECM) becomes more reliable and more comprehensive. This approach enables better understanding of the monitored object of interest, bringing new insights, approaches and also enabling the identification of upgrades requirements, production scheduling optimizations and parameters optimizations. Figure 5 depicts the potential applications of DTS as described by Zhang et al., 2018.

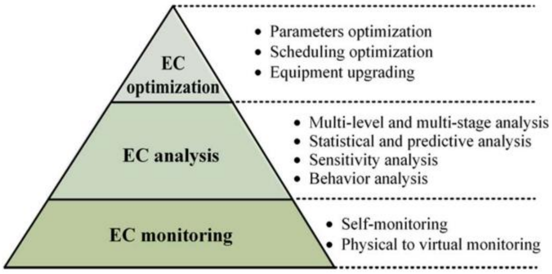

Figure 5 Potential applications of DTS for energy equipment consumption management (EECM) (Zhang et al., 2018)

3.2 Technologies

In this section of the paper, a brief discussion of industry 4.0 and cyber-physical technologies applied to energy efficiency will be discussed and summarized. This adds up to section 3.1 where methods were described, which serve as a fundamental base and potentialized by new emerging technologies such as CPS, I4.0 and digital twin.

3.2.1 Cyber-Physical Systems (CPS)

A cyber-physical system (CPS) is a system that is controlled or monitored by computer-based algorithms, tightly integrated with the Internet and its users. The US National Science Foundation first proposed the term CPS in 2006. In cyber-physical systems, physical and software components are deeply intertwined, each operating on different spatial and temporal scales, exhibiting multiple and distinct behavioral modalities, and interacting with each other in a lot of ways that change with context (Foundation, 2019). Examples of CPS includes smartgrid, autonomous driving systems , medical monitoring, process control systems, robotics systems, pilot avionics and others (Kumar Khaitan Siddhartha ; & D., 2015).

Recently, the cyber-physical system (CPS) and its applications have been widely studied in the field of engineering. Application of a CPS in manufacturing can also be described as a cyber-physical production system (CPPS) which is proposed in process automation and control of dynamic systems. A broader review of the current status and advancement of CPS in manufacturing can be found in many distinct literatures (Wang, L., Torngren, M., Onori, M., 2015). The characteristics of CPS are outlined together with those of big data, cloud technologies and IIoT (Industrial Internet of Things) technologies.

3.2.2 Digital Twin (DT) and Digital twin shop-floor (DTS)

A digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behavior of a physical object (product) or process (value stream) that helps optimize business performance. The digital twin is based on massive, cumulative, real-time, real-world data measurements across an array of dimensions. These measurements can create an evolving profile of the object (product) or process in the digital world that may provide important insights on system performance, leading to actions in the physical world such as a change in product design or manufacturing process. (Deloitte University Press, 2017)

With the development of the digital twin (DT), the concept was then introduced into shop-floor and the digital twin shop-floor (DTS) was proposed in 2017 by (F. Tao, M. Zhang, J. F. Cheng, and Q. L. Qi, 2017). DTS is an extension of DT in the shop floor, aiming at converging the physical and virtual spaces to optimize the existing production activities. It consists of four components, Physical Shop floor (PS), Virtual Shop floor (VS), Shop-floor Service System (SSS) and Shop-floor Digital Twin Data (SDTD). Under this environment, the Equipment Energy Consumption Management (EECM) framework and the potential can also be explored (Zhang et al., 2018).

3.2.3 Industrial Internet of Things (IIoT)

Internet of Things (IoT) is a system of interrelated computing devices, mechanical and digital machines, objects, animals or people that are provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction. The Industrial Internet of Things (IIoT) takes advantage of the IoT connectivity in order to enhance the performance of smart manufacturing and enables the further implementation of industry 4.0 technologies.

3.2.4 Big Data

Big data is a term often used to describe sets of data characterized by high volume, high velocity, and high variety (De Mauro, 2015), and for which the use of advanced analytical tools is required in order to process data into actionable information by identifying patterns, trends, and relationships (Lycett, 2013).

Big data is a consequence of the continuous and increasing production of data, spurred in particular by the vast deployment of digital platforms and applications in everyday life. It is estimated that less than 1 % of all available data is currently analyzed (Gantz, J. & Reinsel, 2012). Big data therefore creates important challenges and opportunities now and in the coming years.

Big data could support sustainability, for instance by helping produce relevant statistics that enable better informed decision making as much on economic, environmental or societal issues (Nagasawa et al., 2017).

3.3 Applications

In this section 3.3, a brief summary is brought in identification and application cases of energy efficiency potentials in manufacturing with the usage of energy efficiency methodologies (section 3.1) and smart manufacturing technologies (section 3.2).

3.3.1 Machine parameters, process and scheduling optimization for Energy Efficiency with CPS application

One relevant application of CPS technology for energy efficiency improvement in manufacturing companies is the integrated energy efficiency optimization strategy and modelling (Li, He, & Li, 2019). The modelling can be divided into four main modelling strategies:

- Energy consumption modelling for machining parameter optimization
- Energy consumption modelling for process planning optimization
- Energy consumption modelling for scheduling optimization
- Energy consumption modelling for tool path optimization

3.3.2 Schedule optimization

Utilizing methods and technologies for energy consumption optimization can provide several opportunities for the production environment. Another opportunity that can be mentioned is the power demand optimization. Utilizing the simulation of the production with an energy model as a base, the work schedule of every machine can be changed in order of lowering the demand during peak hours which could lead to savings in costs even if more production hours are needed.

By studying such possibilities of schedule, the simulation can be utilized to provide scheduling optimization of the production cells, in which the energy consumption can be the determining factor.

3.3.3 Load management

Another relevant aspect of energy efficiency and energy storage in the manufacturing sector is the possibility of managing peak loads, in order to reduce the costs of energy transmission and usage on times of day when energy is cheaper in the market. That becomes also very relevant with the emergence of smart grids and distributed energy generation technologies.

An interesting usage of energy efficiency simulation and CPS in smart manufacturing is to reduce peak loads with a better understanding of the energy consumption profiles of machinery and value streams in a factory. An interesting application framework can be seen found in (Kohl, Spreng, & Franke, 2014).

3.3.4 Shutdown Management

Another identified opportunity is the monitoring of shutdown management of equipment. Some machines are maintained on a working state even though they are not producing. The solution to this problem can be solved by having a real-time monitoring system coupled with a base-line simulation of the distinct consumption levels of the machine in distinct operating modes. Adding a shutdown management program to value streams and production cells can greatly reduce energy consumption reducing waste in terms of energy demand.

With the possibility of measuring the direct consumption of the machines, the opportunity of the indirect energy (ventilation, lighting, water towers…) consumption analysis also appears. With the energy consumption data of the machines, it is possible in real time to reduce the power of ventilation motors in order to save energy. Premises can be defined such as: proportional degree of power could be displayed by the ventilation motors according to the energy demand that the machines display, or even shutting down sections of the factory ventilation system if the machines power demand is low enough. Such opportunities can help making products more competitive and can prolong the lifetime of those indirect systems.

3.3.5 Maintenance Management

The Digital Twin (DT) used together with measurement instruments of high precision can provide a base line for optimal tool mileage, so that when tools become duller its energy consumption increases. By defining an average consumption with the DT and measuring the power consumption in real time, it is possible to set alerts requiring maintenance/change of a specific tool. Nevertheless, the average consumption can also be used to identify problems in the machine and in other parts such as engines by measuring a general difference in consumption that cannot be related in a specific tool path.

This maintenance analysis can be further used as a base for adding new improvements to the machining process, becoming easier to track differences in changes on the process or the machine.

With the measurement of energy consumption in real time allied with other parameters such as maintenance disturbances, tool consumption, temperature, pressure and other aggregates sensors, it is possible to predict when a failure might occur or even showing value of correlations that could not be possible without a big data of multiple machines' parameters.

4. CONCLUSIONS

As previously discussed, energy efficiency has a major importance and relevance for the future of sustainable manufacturing, with growing/increasing importance in achieving the United Nations sustainable development goals (SDGs). In this brief review work, the main objectives were to answer three research questions as defined in section 1. Research questions Q1 and Q2 can be answered through the exploration of the methodologies and technologies applied to improve energy efficiency in the industry 4.0 context in order to achieve a sustainable and smart manufacturing (section 3.1 and 3.2 respectively). To answer research question Q3 use cases were identified (section 3.3) where the application of compatible energy efficiency methodologies and smart manufacturing technologies, such as CPS and digital twin, were critical for the success achievement, enabling and potentializing results. As a summary for answering questions 1 to 3 appendix A brings a consolidated vision of the filtered repertory referred correlating the publications to topics it addresses.

To achieve a lower energy consumption in industry however, it is not enough only applying the correct technical and methodological aspects. A critical element that cannot be left aside is the detailed analysis of the engagement and training of employees on the topic, which is of utmost importance for a successful achievement of good results in energy efficiency in any context. In that regard this topic was not an explored element in this specific work, and can be a further investigation focus. One good reference approach can be the learning factory, which has an applied case in energy efficiency found in the work of (Abele, Bauerdick, Strobel, & Panten, 2016).

5. REFERENCES

Abele, E., Bauerdick, C. J. H., Strobel, N., & Panten, N. (2016). ETA Learning Factory: A Holistic Concept for Teaching Energy Efficiency in Production. *Procedia CIRP*, *54*(Section 3), 83–88. https://doi.org/10.1016/j.procir.2016.06.051

De Mauro, A. et al. 2015. (2015). " What is big data? A consensual definition and a review of key research topics." *AIP Conference Proceedings, 1644: 97., Available*.

Deloitte University Press. (2017). *Industry 4.0 and the digital twin*.

Demichela, M., Baldissone, G., & Darabnia, B. (2018). Using field data for energy efficiency based on maintenance and operational optimisation. A step towards PHM in process plants. *Processes*, *6*(3). https://doi.org/10.3390/pr6030025

ENSSLIN, L., ENSSLIN, S. R., LACERDA, R. T. O., & TASCA, J. E. (2010). *Processo de Análise Sistêmica. Processo técnico com patente de registro pendente junto ao INPI.*

F. Tao, M. Zhang, J. F. Cheng, and Q. L. Qi. (2017). "Digital twin workshop: a new paradigm for future workshop,." *Computer Integrated Manufaturing System*, *23*, *n*, 1–9.

Feng, Y, Wang, Q., Gao, Y., Cheng, J., & Tan, J. (2018). Energy-Efficient Job-Shop Dynamic Scheduling System Based on the Cyber-Physical Energy-Monitoring System. *IEEE Access*, *6*, 52238–52247. https://doi.org/10.1109/ACCESS.2018.2869048

Foundation, U. N. S. (2019). *Cyber-Physical Systems (CPS)*. 1–27. Retrieved from https://www.nsf.gov/pubs/2019/nsf19553/nsf19553.pdf

Gantz, J. & Reinsel, D. 2012. (2012). "The digital universe in 2020: big data, bigger digital shadows, and biggest growth in the far east." *IDC IView*.

Hoang, A., Do, P., & Iung, B. (2016). Prognostics on energy efficiency performance for maintenance decision-making: Application to industrial platform TELMA. *Proceedings of 2015 Prognostics and System Health Management Conference, PHM 2015*. https://doi.org/10.1109/PHM.2015.7380096

International Organization for Standardization. (2018). ISO 50001:2018 Energy management systems - Requirements with guidance for use. *International Organization for Standardization*.

Kohl, J., Spreng, S., & Franke, J. (2014). Discrete event simulation of individual energy consumption for productvarieties. *Procedia CIRP*, *17*, 517–522. https://doi.org/10.1016/j.procir.2014.01.088

Kumar Khaitan Siddhartha ;, & D., M. J. (2015). Design Techniques and Applications of Cyber Physical Systems: A Survey. *IEEE Systems Journal*, 1–15. Retrieved from https://www.academia.edu/23178627/Design_Techniques_and_Applications_of_Cyber_Physical_Systems_A_Survey

Li, X. X., He, F. Z., & Li, W. D. (2019). A cloud-terminal-based cyber-physical system architecture for energy efficient machining process optimization. *Journal of Ambient Intelligence and Humanized Computing*, *10*(3), 1049–1064. https://doi.org/10.1007/s12652-018-0832-1

Lycett, M. 2013. (2013). " 'Datafication': making sense of (big) data in a complex world." *European Journal of Information Systems. 22: 381-386. Available at: Https://Link.Springer.Com/ Article/10.1057%2Fejis.2013.10 [Accessed: 26 April 2017] Marscheider-Weidemann,.*

Ma, S., Zhang, Y., Lv, J., Yang, H., & Wu, J. (2019). Energy-cyber-physical system enabled management for energy-intensive manufacturing industries. *Journal of Cleaner Production*, *226*, 892–903. https://doi.org/10.1016/j.jclepro.2019.04.134

Mahamud, R., Li, W., & Kara, S. (2017). Energy characterisation and benchmarking of factories. *CIRP Annals - Manufacturing Technology*, *66*(1), 457–460. https://doi.org/10.1016/j.cirp.2017.04.010

May, G., Barletta, I., Stahl, B., & Taisch, M. (2015). Energy management in production: A novel method to develop key performance indicators for improving energy efficiency. *Applied Energy*, *149*(2015), 46–61. https://doi.org/10.1016/j.apenergy.2015.03.065

Nagasawa, T., Pillay, C., Beier, G., Fritzsche, K., Pougel, F., Takama, T., … Bobashev, I. (2017). *Accelerating clean energy through Industry 4.0: Manufacturing the next Revolution*. 56. Retrieved from https://www.unido.org/sites/default/files/2017-08/REPORT_Accelerating_clean_energy_through_Industry_4.0.Final_0.pdf

Paper, C., Ferrera, E., Rossini, R., & Evans, S. (2017). *Toward Industry 4 . 0 : Efficient and Sustainable Manufacturing Leveraging Toward Industry 4 . 0 : Efficient and Sustainable Manufacturing leveraging MAESTRI Total Efficiency Framework*. (August). https://doi.org/10.1007/978-3-319-57078-5

Ranganadham, M. V. S. (2018). *Energy Statistics*. 101. Retrieved from http://mospi.nic.in/sites/default/files/publication_reports/Energy_Statistics_2018.pdf

Seow, Y., & Rahimifard, S. (2011). A framework for modelling energy consumption within manufacturing systems. *CIRP Journal of Manufacturing Science and Technology*, *4*(3), 258–264. https://doi.org/10.1016/j.cirpj.2011.03.007

US Environmental Protection Agency. (2010). *"Defining Life Cycle Assessment (LCA)."*

Wang, L., Torngren, M., Onori, M., 2015. (2015). *Current status and advancement of cyber- physical systems in manufacturing.*

Zhang, M., Zuo, Y., & Tao, F. (2018). Equipment energy consumption management in digital twin shop-floor: A framework and potential applications. *ICNSC 2018 - 15th IEEE International Conference on Networking, Sensing and Control*, 1–5. https://doi.org/10.1109/ICNSC.2018.8361272

Zhou, L., Li, J., Li, F., Meng, Q., Li, J., & Xu, X. (2016). Energy consumption model and energy efficiency of machine tools: A comprehensive literature review. *Journal of Cleaner Production*, *112*(2014), 3721–3734. https://doi.org/10.1016/j.jclepro.2015.05.093

6. RESPONSIBILITY NOTICE

The author(s) is (are) the only responsible for the printed material included in this paper.