Exploiting data analytics for improved energy management decision-making

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Abstract: The adoption of Internet of Things and Cloud technologies in the context of Industry 4.0 provides manufacturing industries with the opportunity to collect data from multiple sources. Analytical tools and techniques can be then applied to support decision-making processes with valuable information. Industry 4.0 technologies have been implemented in many sectors and industries: among them, energy management - often representing one of the main costs for manufacturing companies - is considered in this study. The aim of this paper is to contribute to the understanding of how the implementation of Industry 4.0 technologies and, in particular, the analysis of energy consumption data, can change or enable decision-making thereby improving energy management. Based on a literature review and current practices, possible applications of data analytics in the energy management field are proposed and several energy management decision areas are discussed. The paper includes a case study aiming at illustrating how the implementation of Industry 4.0 technologies, supported by proper strategical and operational approaches can improve energy management integrating energy consumption data with other sources of data.

Keywords: Energy management, data analytics, decision-making, Industry 4.0

1. Introduction

Energy efficiency represents an increasingly important leverage to achieve financial, social and environmental enhancement (Trianni et al. 2019) and a large academic literature is dedicated to energy efficiency strategies both at macro levels, such as at industry, regional or state level and at micro level, considering energy management for site, building and processes. Focusing on the industrial and manufacturing domain, energy management specifically refers to the supply, the conversion and utilization of energy (O'Callaghan and Probert 1977) and may include lot of different practices ranging from the definition of the best energy source, to the identification of energy waste, to the optimization of energy consumption during production. The adoption of those practices and their successful implementation is the result of a decision-making process both at a strategic level, considering the best strategy to adopt and at operational levels, considering more punctual and operative actions.
Industry 4.0 technologies, particularly Internet of things (IoT), enables the support and enhancement of energy consumption awareness (Shrouf and Miragliotta 2015). Indeed, the adoption of real-time energy monitoring systems enables firms to better understand their energy consumption. Moreover, integrating energy data with other sources (e.g. on production, processes etc.) can actively support decision-making in the energy management, both at the operational level and in strategic evaluations (Bevilacqua et al. 2017). However, the research in decision-making related to energy management in manufacturing seems not yet well established (Zhu et al. 2015).
This paper aims at revising the opportunities that data collection enabled by the adoption of technology along with the use of analytics can bring to decision-makers in the context of energy efficiency in manufacturing. In particular, it explores how different approaches to data analysis (descriptive, predictive, and prescriptive) may influence different manufacturing decision areas which impact energy consumption and efficiency.
The paper is structured as follow: Section 2 discusses the literature background about on energy management in manufacturing, presenting how data can support it. Section 3 introduces the decision-making processes involved in the energy management sector, while Section 4 presents a classification of different energy management practices in which data analytics may enhance decision-making. Section 5 presents a case study on an Italian manufacturing company, which is exploring data potentials in energy management. Section 6 presents the conclusion, including limitations and further developments.

2. Literature background: Energy Management

In the past decade, research on energy management in business practice at different levels has been increasingly conducted. This can be partially attributed to the increasing relevance of sustainable manufacturing principles. Several studies have been performed in various domains, ranging from energy audit practices and the assessment of audit plans (Fleiter et al. 2012), to the development and evaluation of energy industrial policy (Tanaka 2011), energy and process optimization adopting statistical modelling (Giacone and Mancò 2012), and energy efficiency-based maintenance (Kaman 2002).

The O'Callaghan and Probert (1977) definition of energy management underlines the fundamental role of data in the energy management process: indeed, it "*involves monitoring, measuring, recording, analysing, critically examining, controlling and redirecting energy and material flows through systems so that least power is expended to achieve worthwhile aims*". In accordance with this characterization, several works in literature include different practices, which require collection and analysis of energy consumption data integrated with other sources. One of the fundamental and underlying component towards energy efficiency enhancement is the adoption of energy monitoring systems (Kannan and Boie 2003), which can lead to an increment in energy consumption awareness. Moreover, also notable standards like ISO 50001 defined energy monitoring and measuring systems as the top activity needed to achieve energy efficiency, and clearly refers to statistical model and forecasting as possible approaches to reduce energy consumption.

Nevertheless, the adoption of energy efficiency management in industries is still unexploited at its full potential, as defined in the so-called "energy efficiency gap" (Lee 2015). This low level of implementation rates has been widely discussed considering barriers, drivers and decision-making procedures that affect investments in energy management.

In this context, low-cost sensing technologies and Internet of Thing paradigm are key to enhance energy efficient practices in manufacturing. Advancement in new sensing methods, real-time analysis, connectivity, and the possibility to integrate new cyber technologies enable a continuous monitoring of energy consumption and an autonomous evaluation of machine health and functioning, allowing an efficient energy management (Edgar and Pistikopoulos 2018). Indeed, the availability of real-time energy consumption data creates optimization opportunities: data analysis and mathematical models can enhance practices in production management. Recent studies successfully demonstrate how the adoption of technologies like IoT, Cyber Physical Systems (CPS), Big Data analytics, and machine learning algorithms may improve manufacturing energy management, working on their production processes. (Giacone and Mancò 2012; Kaman 2002; Liang et al. 2018; Zhang et al. 2017) propose a green energy management scheduling to enhance energy efficiency at production level; Liang et al. (2018) propose a novel process of dynamic scheduling which also considers energy efficient optimization over manufacturing lifecycles. Other studies present frameworks of self-adaptive systems able to allocate energy and resources timely either at shop floor level (Zhang et al. 2017) or at production-logistics level for material handling (Zhang et al. 2018).

2.1 Data analytics support for energy management

The possibility to gather accurate, real-time data leveraging on Industry 4.0 technologies creates a potential in the implementation of energy management initiatives. Nevertheless, understanding how this data should be analysed, provided and showed to a final user to reduce energy consumption or increase energy efficiency is a relevant topic. The implementation of an Industry 4.0 energy management system also needs the right supportive architecture, represented by three different layers: (i) infrastructure, (ii) computing, and (iii) application (Figure 1) (Hu et al. 2014).

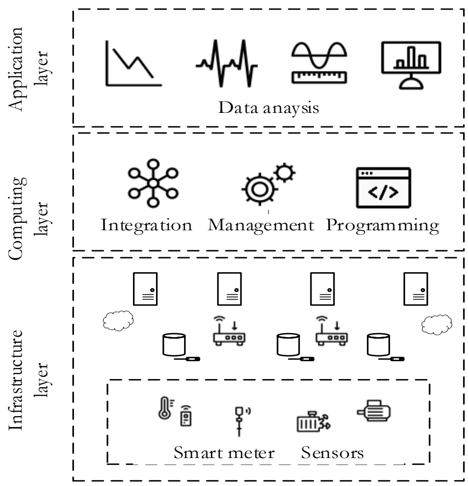

Figure 1: Architecture for big data system in energy management (adapted from Hu et al. (2014))

Considering the focus of our research, the infrastructure layer also concerns all the hardware needed to collect energy consumption data. In this way the infrastructure layer includes hardware components needed to capture data, such as sensors, smart meters, and ICT resources, which can be organized by cloud infrastructure and enabled by virtualization technology.

The computing layer encapsulates different software tools that run over the hardware infrastructure. It comprises data integration, programming model, which implement abstraction application logic (e.g. MapReduce, Pregel) and data management. The application layer exploits the interface provided by the programming models to implement various data analysis functions.

With regard to the application layer, it is possible to define different degrees of complexity based on data analytics approaches which, according to the analytics taxonomy, can be divided into descriptive, predictive, and prescriptive (Wang et al. 2016). Depending on those different approaches, data analytics techniques may impact at different extent on the processes of knowledge creation and decision making. Particularly, predictive and prescriptive analytics play a vital role in helping companies make effective decisions on the strategic and operational direction of the organization (Demirkan and Delen 2013). Specifically:

(a) *Descriptive analytics* refers to historical or real-time data analysis yielding information on what happened or is currently happening for reporting and monitoring purpose. General tools adopted are traditional mathematics and statistics. Descriptive analytics comprises also deeper analysis aimed at understand why things happened or are happening. For example, machine learning approaches, data mining and statistic are adopted to perform regressions, cluster analysis, anomaly detection and benchmarking.

(b) *Predictive analytics* refers to the analysis of historical data to provide information on what will happen and why it may happen. General purposes detection of trend and relationships aimed at predicting future behaviour. Hidden patterns discovery could be performed with different techniques, which ranges from statistical analysis and forecasting to machine learning algorithms.

(c) *Prescriptive analytics* refers to utilization of data to provide suggestion on what should be done and why. It is mainly used to assess alternative decisions and determine the best one, minimizing or maximising some specific objective. Mathematical and statistical techniques are complemented with optimization, simulation, multi-criteria decision-making.

Based on the above-mentioned taxonomy and according to further descriptions available in literature (Lustig et al. 2010), Table 1 summarizes the possibilities that data analytics may offer, detailing the purposes of analysis, time span of data (which can contain all historical record or be based on real time analysis), utilization of data, which refers to the output of the analysis and tools that can be used to perform it.

Table 1: Data analytics taxonomy

	Purpose	Time span of data	Data utilization	Methods
Descriptive (DA)	Observation	Historical Real-time	Reporting Monitoring	Mathematics Basic statistics
	Analysis	Historical Real-time	Clustering, Aggregation Regression, Benchmarking Anomaly detection, Benchmarking	Machine learning, Data mining, Statistical models
Predictive (PRA)	Prediction	Historical, Real-time	Forecasting	Statistics, Machine learning, Data/text/web mining
Prescriptive (PSA)	Prescription	Historical, Real-time	What if analysis	Simulation, Optimization, Multi-criteria decision making, Decision modelling, Expert system

3. I4.0-enabled energy management decision-making

The research in decision-making related to energy management in manufacturing is not yet well established (Zhu et al. 2015). Nevertheless, to achieve energy efficiency in manufacturing, industrial stakeholders need to apply proper strategies and make operational decisions. In particular, energy management approach needs to be aligned with corporate goals (May et al. 2013) and requires to be embedded in the strategic decision-making of the enterprise to be effective.

Actually, energy management strategies reflect several decisions at both long and short term. Long-term decisions concern general aspects of the enterprise, such as standards and policies, investments, long-term corporate initiatives, as well as technology selection and development, strictly related to product and process design (May et al. 2017). On the other side, short-term decisions involve all the actions that impact quickly on the operational activities of the enterprise, requiring flexibility and responsiveness to ensure energy efficiency. Aligning operational production processes with energy efficiency practices is considered crucial as well as integrating energy efficiency in product and process design (May et al. 2013).

Industry 4.0 technologies, IoT and Data Management in particular, can actively support decision-making in the energy management, providing decision makers with an increased awareness about energy consumption (Bevilacqua et al. 2017). According to the data infrastructure discussed in Section 2, in the application layer, several descriptive, predictive, and prescriptive analytics can be developed to support the long- and short-term approaches in energy management related decision-making.

Qin et al. (2018) propose a classification of energy management applications, distinguishing:

- Process oriented applications (POA), which directly affect production parameters through automatic control signals;
- Operator oriented applications (OOA), which provide human workers with real-time production energy data;
- Enterprise oriented applications (EOA), which concerns more general system lifecycle analysis and energy sustainability analysis.

In the first class, POA are mainly related to automatic control systems than can be embedded in production processes to allow real-time feedback actions based on data analysis. Industry 4.0 technologies support this kind of application with Cyber-Physical Systems theory and implementation. On the other side, in OOA and EOA, the focus is on tools that can proactively support human decision makers to take actions aligned with energy efficiency objectives. OOA and EOA can be connected with long-term and short-term decisions concerning energy management strategy and operations. Moreover, all these kinds of applications can be implemented in different areas of the enterprise, such as maintenance management, inbound logistics, production planning and scheduling, manufacturing process design and configuration (Shrouf and Miragliotta 2015).

Energy management decisions are reflected in Energy Management Practices (EMP) which can be based on different types of applications, and are implemented in several areas of the manufacturing process. An EMP is defined as "*a technique, method, procedure, routine or rule adopted at a precise stage of the industrial energy management setting in order to achieve the company's energy efficiency objectives. It acts on technological, non-technological, or of support aspects, by improving the energy performance directly or indirectly in a specific area of the company.*" (Trianni et al. 2019). Thus, EMP can affect different stages of the process lifecycle, from the design and configuration phase, to the maintenance activities need to ensure a proper availability and functioning of the system.

4. Data-driven energy management decisions

From the analysis of several EMPs formalized and classified in literature (Sa et al. 2015; Trianni et al. 2019), a set of practices which can be relevantly affected by data analytics has been selected and reported in Table 2. Among all the proposed practices of literature, a set of fourteen EM practices have been chosen in relation to the relevance of data utilization for their effective deployment in the factories. In particular, the table shows the short- and long-term decisions related to EMPs, along with the most suitable data analytics approaches to support them.

Based on the data classified proposed by Shrouf and Miragliotta (2015) as relevant data enabling energy management practices, seven classes of data have been elaborated and defined as follow:

(1) Machines technical data (e.g., process parameters, such as temperature, velocity)
(2) Production management data (e.g., products, quantity, lot sequencing)
(3) Product data (e.g., manufacturing cycle, bill of materials)
(4) Economic data (e.g., energy cost, contracts)
(5) Maintenance data (e.g., mean time between failure, mean time to repair)
(6) Environmental data (e.g., weather, external temperatures)
(7) Regulations data (e.g., internal policies, standards)

For each practice, in the last column of Table 2, suggestions about data that could be integrated with energy consumption data are provided based on several contributions presenting specific application of data-driven energy management practices (e.g., Giacone and Mancò 2012; Kaman 2002; Liang et al. 2018; Zhang et al. 2017).

Looking at Table 2**Error! Reference source not found.**, it is noteworthy that for short-term decisions, both POA and OOA are appropriate, because corrective actions to the operational state of the systems can be implemented by automatic control or by direct control performed by operators, based on data observation and analysis. Conversely, in a long-term approach, decisions are always performed by humans, because general objectives and system constraints need to be evaluated. For this reason, EOA can provide suitable decision support.

Table 2 shows that similar decision areas can be found in short- and long-term decisions but with two different aims. Long-term decisions concern the definition and configuration of the functioning rules of the system, while short-term decisions aim at aligning the operations to the energy consumption target that has been fixed by the company. For instance, at strategic level, an enterprise is required to take a decision about energy suppliers, also considering if green energy could be provided by renewable sources. Such decisions are taken in the development phase of a new plant or during a new process design. Several scenarios can be considered through simulation tools, which enable what-if analysis of different solutions (i.e., prescriptive analytics). During the daily operations of the production, then, the company can decide to adopt a demand response approach, with a real-time evaluation of the best energy supplier for that specific time frame, supported by machine learning techniques (i.e., descriptive analytics) or forecasting models (i.e., predictive analytics).

Similarly, in a process development phase, energy efficient equipment can be designed and conceived in order to ensure low energy consumption using simulation and optimization tools based on virtual models; multi-criteria decision support systems can be employed to compare different solutions as well (i.e., prescriptive analytics). Once the process/machine/equipment is installed in the shop floor for the production, process parameters variation can be used to regulate the behaviour of the machines according to contingencies, such as the manufactured products, the available energy source or the human operator needs. The same considerations can be applied to internal logistics organization, maintenance management, production planning and scheduling, etc.

Finally, from Table 2, it is possible to notice that for short-term EM decisions data about technical parameters, as well as processes and production data are mainly required to control the energy consumption of the manufacturing system and arrange the management of production and auxiliary activities (such as maintenance and internal logistics). Conversely, long-term decisions generally involve more data. In particular, regulations and policies have to be taken in consideration at any time when defining targets (e.g., performance targets), procurement strategies, and system design.

Further, economic data are required for almost all the EMPs, since all the practices aim at reducing the total cost related to energy consumption. To gain efficiency and consequently reduce costs, the decision-making needs to evaluate possible alternatives comparing energy cost, regardless of the fact that it concerns an operational condition (e.g., production sequence, process parameters, etc.) or a general strategy.

Table 2: Energy management decision classification

		DATA UTILIZATION		DATA TO INTEGRATE
Short-term POA - OOA	Control and optimization of operational parameters	DA	Analysis	(1), (2), (3)
	Monitoring and evaluation of energy performance and energy data	DA	Observation Analysis	(2), (4)
	Demand side management	DA PRA	Analysis Prediction	(2), (4), (6), (7)
	Energy efficiency-based maintenance	DA PRA	Analysis Prediction	(1), (2), (3), (4), (5), (7)
	Energy-aware product scheduling	DA	Observation Analysis	(1), (2), (3), (4), (5), (6), (7)
	Reducing idle time by switching a machine off	DA	Observation Analysis	(1), (2), (4)
Long-term EOA	Definition of energy efficiency KPI	DA	Observation Analysis	(1), (2), (3), (4), (5), (6), (7)
	Definition of targets	PSA PRA	Prescriptive Predictive	(1), (2), (3), (4), (5), (6), (7)
	Energy demand budgeting	PSA PRA	Prescriptive Predictive	(2), (4), (6), (7)
	Energy efficient procurement of equipment and materials	PSA	Prescriptive	(1), (3), (4), (7)
	Energy-efficient system/process/equipment design	PSA	Prescriptive	(1), (3), (4), (7)
	Definition of energy source	PSA	Prescriptive	(2), (4), (6), (7)
	Determination of internal logistics	PSA	Prescriptive	(1), (2), (3), (4), (5), (7)
	Definition of maintenance strategies	PSA	Prescriptive	(1), (2), (3), (4), (5), (7)

4. Case study: company Alpha

To better evaluate the impacts of data utilization in a real manufacturing context, a case study has been developed in a textile company, located in the North of Italy. An interview has been performed by the researchers to the IT and Operations managers of the company, in order to investigate how the implementation of new technology, and in particular data analytics, can improve EM strategies and decisions.

Company Alpha is one of the world's leader manufacturer of printed and jacquard fabrics for luxury brands. It manufactures and distributes internationally fabrics and finished accessories (e.g., ties, scarves) which are produced worldwide in several plants of the group. In the Italian plant, company Alpha carries out the entire production process, from the initial development and design of fabrics, to the weaving, dyeing, printing, and finishing phases.

The production process is complex, involving many automatic machines, but also requiring fine manual activities that are still performed by specialized operators. Several production processes are characterized by high energy consumption. In fact, to ensure the quality of the fabrics as required by customers, production phases, such as washing or steaming, always occur within controlled parameters that must be guaranteed. For instance, in the steaming phase, high quantity of energy is consumed to maintain constant temperatures, which are measured by sensors at different positions on the fabrics during the process. The same issues concern other production phases (e.g., washing tanks), generating in the whole plant a huge energy consumption, which results in high energy costs for the company.

In recent years, company Alpha started developing some strategies to reduce the energy consumption, mainly replacing old equipment with new efficient ones, and installing a photovoltaic system to produce a part of the needed electricity. At the same time, the company has developed an internal policy supporting the environment sustainability to comply with external standards. However, in the current state, company Alpha is facing several barriers in implementing more effective energy management strategies to reduce the energy cost, principally related to the impossibility to retrieve data about single machines energy consumption. Moreover, the company is currently not able to have a single piece traceability that could link the products to the timeframe and machines where they have been manufactured.

Currently, exploiting the potentials of Industry 4.0, company Alpha is investing in new technologies to improve the production and energy performances. In particular, the following improvement has been envisioned for the TO-BE state:

1. Machine networking and real-time data acquisition (i.e., technical data and energy consumption data for each machine)
2. MES implementation to collect and organize production and process data
3. Single-piece traceability with RFID technologies

To reach the TO-BE state, the company is developing an IoT infrastructure to collect data from machines, along with a Cloud platform to store and share data. Thanks to these advances, new EM opportunities open up for the company. Indeed, the possibility to apply data analysis techniques can enable more aware decisions about the EM practices to put in place to reduce the total energy cost. Based on the classification provided in Table 2, the data-driven EM decisions suitable for the implementation in company Alpha are depicted in Table 3. Two steps of implementation are depicted, based on the data that company should integrate in the near future to improve the EM performances:

- In Step 1, short-term EM practices such as monitoring and controlling of operational parameters can be implemented. For instance, descriptive analytics on the energy consumption related to a specific product can enable parameters' variation in the machine recipes to decrease the energy consumed, always ensuring the required quality for the product.
- In Step 2, energy-efficient procurement and system design can be achieved, linking operational production data with the standards defined by the company.

According to the information provided, the company is not planning to integrate maintenance and environmental data; therefore, EM practices to improve maintenance and logistics will not be implemented in the near future. Nevertheless, it has been estimated that, based on the available data observation and analysis, it would be possible to define some partial energy efficiency KPI and targets in a long-term perspective.

Table 3: Data-driven EM decision for company Alpha

	EM DECISION	DATA EXAMPLE
Short-term POA - OOA	Control and optimization of operational parameters Monitoring and evaluation of energy performance and energy data Reducing idle time by switching a machine off	- Timestamp, - Machine ID no., - Recipe ID, - Batch no., - Product code, - Production meters - Energy consumption, - Process temperature
Long-term EOA	Energy efficient procurement of equipment and materials Energy-efficient system/process/equipment design	- Machine ID no., - Recipe ID, - Batch no., - Product code, - Production meters - Machine states - Energy consumption, - Water consumption, - Process temperature

By implementing new technologies, company Alpha is expecting benefits in the total energy costs of its factory, along with an improvement in the sustainable design of production processes and supply chain. In fact, in the current state, company Alpha is not undertaking any action to minimize the energy cost. The case study aims at showing how the new technologies introduction in manufacturing firms, which supports many areas of the factory management, can effectively create profitable opportunities to upgrade the energy management as well. With the support of the proposed EM decision classification, indeed, the case study outlines how the implementation steps of data-driven EM practices need to be aligned to the company development strategy towards Industry 4.0. In fact, different approaches in energy consumption reduction can be applied in relation to the development of infrastructures and applications that are planned by company regardless the specific EM area.

5. Conclusions

Starting from the consideration that EM practices can benefit from the adoption of energy monitoring system based on Industry 4.0 technologies, this paper provides an exploration about data utilization in the EM decision-making, suggesting how different kinds of data should be integrated to support EM practices, finally presenting a case study developed in a manufacturing company. The paper provides a contribution to the managerial community shedding light on the opportunities that data analytics can bring to EM decisions and practices. Further developments of these research can be envisioned. First, a multiple case study approach can be carried out in other firms, to test if the suggested data utilizations are aligned with the EM practices. Also a longitudinal case study in company Alpha could contribute to validate the framework presented in Table 2. Finally, specific data application can be developed, for instance exploiting data acquired by real production systems in descriptive or predictive analytics supporting real-time reconfiguration of process parameters.

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