Energy management based on Internet of Things: practices and framework for adoption in production management

Fadi Shrouf [a, b, *], Giovanni Miragliotta [a]

[a] Department of Management, Economics and Industrial Engineering, Politecnico di Milano (POLIMI), Italy
[b] Department of Industrial Engineering, Business Administration and Statistics, ETSII, Universidad Politécnica de Madrid (UPM), Spain

Received 6 November 2014
Received in revised form
5 March 2015
Accepted 18 March 2015
Available online 27 March 2015

1. Introduction

Today, energy-efficient manufacturing processes provide several advantages to manufacturing companies, such as cost saving notwithstanding rising and volatile energy prices, building a good reputation through the fulfillment of governmental and international environmental regulations, and adapting to the changes in consumer perception toward green products. Garetti and Taisch (2012) define green products as those that have been manufactured while consuming as little energy as possible — not just products which consume less energy when used by the customer. Conse-quently, the best practices that aim to reduce energy consumption during production are increasingly important to today's manufacturing companies.

In many factories, energy management practices at production levels suffer due to lack of awareness of energy consumption behavior. In fact, energy savings are expected to be achievable both from improvements in energy efficiency of specific production processes, as well as from the usage of innovative energy monitoring systems and management approaches (Weinert et al., 2011).

New emerging autonomous technologies, such as Internet of Things (IoT), are enhancing monitoring of production processes (almost) in real-time. An area where IoT plays a major role is in the monitoring of energy consumption (Haller et al., 2009). IoT technology (e.g. smart meters and sensors) provide awareness of energy consumption patterns by collecting real-time energy consumption data.

The availability of real-time energy consumption data offers several opportunities to reduce energy consumption by enabling and enhancing energy-efficient practices in production management. The focus of this research is to understand the benefits of integrating such energy data in production management decisions regarding discrete manufacturing, and to identify production

* Corresponding author. Department of Management, Economics and Industrial Engineering, Politecnico di Milano (POLIMI), Italy.
E-mail addresses: fadi.shrouf@polimi.it (F. Shrouf), giovanni.miragliotta@polimi.it (G. Miragliotta).

management practices that can be enhanced or enabled by this integration.

Given these introductory remarks, the paper is structured as follows: Section 2 describes the research methodology; Section 3 provides a review of state-of-the-art energy management practices, both academic and business-wide. In particular, a description of a general IoT architecture for energy monitoring systems is provided at the end of Section 3. Based on improved energy consumption awareness, Section 4 illustrates energy management practices that are enhanced and enabled by adopting IoT. Section 5 then presents a framework for energy management based on the integration of energy data coming from IoT devices. Finally, Section 6 presents managerial recommendations and some concluding remarks on research outcomes, limitations and its future developments.

2. Research methodology

Fig. 1 illustrates the research design adopted in this study. First, a systematic literature review of concepts and theoretical frameworks on energy management practices and the IoT paradigm was conducted. This included critical evaluation of IoT definitions, technologies and factory applications. For this purpose, several keywords were used in the search process, such as “energy management practices,” “energy efficiency in production,” “energy monitoring,” “energy consumption awareness,” “energy data in real-time,” “smart meters,” “IoT technology,” and “IoT and energy efficiency.” Related papers were found using search engines, including Google Scholar, Web of Knowledge, Elsevier, and Scopus.

Second, given the nature of this research paper, a qualitative research approach based on semi-structured interviews was used: the interview format provided a level of structure in order to cover some main topics, but left a certain degree of flexibility by allowing for follow-up questions in order to provide clarification (Saunders et al., 2009).

Namely, six executives of Technology/Solutions Providers were interviewed: two general managers, two sales managers, one account manager and one product manager. These types of companies are regularly in contact with their customers and provide services for them, such as storing customers' data in the cloud and analyzing such data: the interviewees can thus be classified as experts in energy management practices. Interviewing experts is commonly used in the literature, as in Koskela (2011). The interviewees were asked different questions to highlight the state of the smart meters, sensors, and applications they offer to customers. In addition, they were asked to define their customers' practices in energy management after installing smart meters and collecting and analyzing energy data. These questions were guided by the literature review performed in Step One, and pro-vided insight into the current sustainable practices at manufacturing companies and opportunities for improvements based on the availability of energy consumption data. Moreover, following the methodology in (Koskela, 2011), four further interviews were conducted with industry professionals. Two of them were experts in IoT technology; they were asked questions focusing on IoT technology and its applications for energy management. The other two were energy management consultants, who were asked about current energy management practices and integrated energy data in production decisions at the production level.

Third, we collected information available online from ten manufacturing companies that have already adopted IoT technology for energy efficiency. The information collected included which technology had been installed and which energy management practices were adopted after collecting and analyzing energy data, and which benefits they observed.

Eventually, relying on the literature review and interviews, inductive modeling was adopted to build a framework for IoT-based energy management in production, so as to define how energy information could be integrated into production management decisions. In order to test the validity of the framework, it was reviewed by three energy management consultants (two experts from the interviewees mentioned before, plus an additional third reviewer).

3. State of the art

This section presents recent research findings in terms of approaches and principles for energy management in factories, and it discusses current energy data collection methods; then the IoT paradigm is introduced and deepened, with a focus on energy monitoring applications.

3.1. Energy management practices

Recently, researchers and decision-makers in factories have had a common goal of creating goods and services using production systems and processes that are non-polluting, without affecting overall productivity. A comprehensive review of the current state of improving energy efficiency methods and techniques in discrete parts manufacturing has been provided by Duflou et al. (2012). Generally, an energy management program is not only technical, rather multidisciplinary in nature, and it combines management disciplines with engineering skills.

In reality, energy management faces challenges in manufacturing due to the complexity that arises from the variety of energy uses across thousands of processes, each one having unique energy consumption characteristics; in addition one should consider different production requirements based on product, quality, and other business factors (Berglund et al., 2011). The integration of energy management with production management is one of the prominent issues towards enhancing green production systems (Bunse et al., 2011).

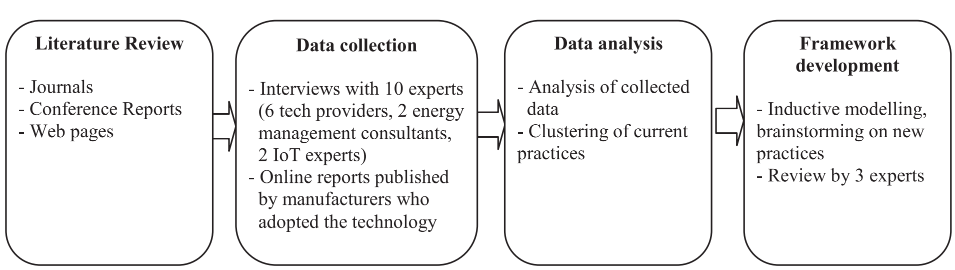

Fig. 1. Research design and methodologies.

Many energy-saving activities that are used in manufacturing companies are presented in Liu et al. (2014). Focusing on the operational level, plenty of literature can be found about the minimization of energy waste during machine idle status (Mouzon et al., 2007), or the avoidance of energy consumption peaks by utilizing load shifting (Herrmann and Thiede, 2009). There is also literature focusing on reducing energy consumption of machine tools (Avram and Xirouchakis, 2011; He et al., 2012), and more recently Despeisse et al. (2013) described several sustainable manufacturing tactics to link high-level sustainability concepts with specific operational practices for resource efficiency in industrial manufacturing.

3.2. Energy monitoring and data collection methods

The availability of energy consumption pattern in near-real-time is essential to realize energy saving opportunities (e.g. load balancing, proactive maintenance). Kannan and Boie (2003) present a structure of an energy management program in factories where the availability of energy consumption data is key to identify the possibilities of energy savings. Gordić et al. (2010) provide a guideline for metalworking industry managers to implement an energy management system based on an energy matrix proposed by EPA Victoria (2002). The matrix shows that using a comprehensive energy monitoring system to identify possibilities for energy savings is a fundamental component in reaching an advanced level of energy management. Also considering the ISO 50001 approach as a reference model, energy monitoring and analysis have been identified as the top activities that need to be performed to improve energy efficiency.

Lack of sub-metering is highlighted as the main barrier to improving energy efficiency in non-energy-intensive manufacturing by Rohdin and Thollander (2006), as well for energy intensive in-dustry by Trianni et al. (2013). This means manufacturing machines and equipment are generally not metered permanently (Müller and Löffler, 2009). Moreover, Garetti and Taisch (2012) indicate that in discrete manufacturing “the current level of control in energy use is very poor or absent.” This has motivated researchers to investigate and propose methods for estimating energy consumption patterns in manufacturing: an example is the “EnergyBlocks” methodology, used to predict accurate energy consumption concerning production operations (Weinert et al., 2011). For example, Vijayaraghavan and Dornfeld (2010) have simulated energy profiles based on the avail-able data of machine tools, and also Hu et al. (2012) proposed an on-line approach for monitoring energy of machine tools without using a torque sensor, based on an energy consumption model of machine tools.

Most of the methods for calculating expected energy consumption (i.e. forecasting models) can be classified into two categories: the first is based on historical data (i.e. comparison with previous periods), while the second is based on driving factors (e.g. planned production quantity). Both methods have weaknesses, such as accuracy, long interval time (i.e. weeks or months), inaccurate results when abnormal consumption patterns occurred during the previous period, inability to spot when energy waste has occurred, etc.

Thus informative, timely and accurate production and energy data are becoming vital in allocating energy consumptions to machines, equipment and processes, and to eliminate waste and determine inefficiencies in production systems. Sensor technology (Bunse and Vodicka, 2010) and energy metering (O'Driscoll and O'Donnell, 2013) are essential for the assessment of energy performance and improvement targets. Power measurement equipment must be installed at diverse levels in the factory in order to collect energy consumption data. Kara et al. (2011) and O'Driscoll & O'Donnell (2013) define three levels of energy metering in factories: first, factory level metering, which is usually installed between the utility provider and the main factory electrical incomer. Second, process chain/production line-level metering, which is useful for production schedules that consider energy consumption and quantify the energy savings achieved after implementing an energy efficiency improvement project. Third, metering at machine level, which provides significant information for each machine, including energy labeling of machine tools and products, average power demand, idle power demand, on/off peak energy usage, energy forecasting in production design and evaluation of local technical improvements. Table 1 shows details of electrical metering applications (based on (Queensland Manufacturers project, 2010).

3.3. The Internet of Things for energy management

The Internet of Things (IoT) expression, first cited in 1999 by Kevin Ashton at the MIT Auto-Id center, is used to refer to a technological revolution expected to impact most life domains. The IoT paradigm is expected to have the same or an even larger impact than the Internet itself, as Gartner (2013) estimates that in 2020, 26 billion objects will be connected to the internet.

3.3.1. What is IoT

According to Miragliotta et al. (2012), the Internet of Things paradigm is defined as the interplay of smart objects and of smart communication networks. On the one hand, a smart object is an object which possesses some mandatory functionalities plus some optional ones: self-awareness encompasses a unique digital identifier (mandatory), self-diagnosis and location awareness; communication (mandatory) with other smart objects and/or with the central acquisition system; interaction (optional) with the surrounding environment (e.g. sensing, metering and actuation); and eventually data processing (optional), i.e. elaboration of the data collected to extract information for more efficient data management and transmission. Objects smartness, therefore, may range from a minimum of a passive RFId (Radio-frequency identification) tag to a maximum of a wireless network of sensors/

Table 1
Details of electrical metering applications.

Application	Feature/Comments
Utility meter	• Measures electricity entering a production site. • Metered quantities correspond with service provider billing. • Consumption either monitored on a regular basis (i.e. monthly or quarterly) or estimated from previous billing. • Maintained by service provider.
Traditional consumption meters	• Measures quantity and cumulative consumption. • Labor intensive, manual meters reading is generally required. Manual metering reading is associated with non-negligible errors. • Low data quality: not available in an appropriate format, and may need manipulation before usage. • Poor data timeliness: not available in real-time
Smart meter (IoT)	• Monitor numerous points within the factory • Continuous measurement. • Automated meter reading. • Multiple parameters metered. • Measure time of use (ToU) consumption for periods such as peak and off-peak. • Computational abilities. • Connected to Energy management system. • Automated and remote meter management.

actuators. On the other hand, a smart network is a communication infrastructure characterized by one or more of the following mandatory functionalities: standardization and openness of the communication standards used, from layers interfacing with the physical world (i.e. tags and sensors) up to the communication layers between nodes and with the Internet; object addressability (direct IP address) and multi-functionality, i.e. the possibility that a network built for one application (e.g. road traffic monitoring) be capable and available for other purposes (e.g. environmental pollution monitoring or traffic safety).

In the manufacturing industry, the IoT is relying on wireless devices such as RFId and wireless sensor networks (Atzori et al., 2010) to gather real-time data from the shop floor, such as a machine status, inventory levels, shipment progress, and, of course, energy consumption data. For this reason, several types of sensors and smart meters are available in the market, both wired and wireless.

3.3.2. *IoT-based energy management technology*

The need for energy consumption awareness has motivated several companies to provide innovative monitoring solutions for the industrial sector, such as EpiSensor, Wi-Lem, Watts Up, SATEC, ReMake Electric, Energy Metering Technology LTD, Socomec, General Electric, Mitsubishi, Siemens, and Schneider. Similarly, several companies provide Enterprise Energy Management (EEM) software applications to analyze the collected data, such as ResourceKraft, Google, eSightenergy, and EFT-energy. By generalizing providers' best practices, a general system architecture for energy monitoring using Internet of Things technology can be derived, as illustrated in Fig. 2.

At the bottom layer of this generalized architecture there are sensors and smart meters, which may be connected through wired or wireless networks. Energy meters available on the market can acquire several parameters (e.g. power consumption, power factor, and max/min of peak voltage), hence they provide a high level of flexibility in monitoring and analyzing energy consumption. A state-of-the-art review of energy meters in manufacturing facilities has been provided by O'Driscoll & O'Donnell (2013). Meters can be used with different monitoring targets, which may be the whole production line, single machines, or even single components.

At the mid layer, collected data are send to a gateway, and then transferred to a local computer or to the internet via standard communications protocols, such as the ZigBee wireless technology (based on IEEE 802.15.4 standard, cf. Alliance ZigBee, 2005), or Wireless Hart. If wireless networks are used, sensors can be even more flexibly placed throughout the shop floor. At this level, the main differences with respect to old, proprietary M2M technologies are represented by the use of Smart Networks as defined in the previous section (standard, open, multifunctional, with direct ob-ject addressability) and by the use of classical web-enabled features (publish/subscribe data access, Software-as-a-Service platforms for the integration of data coming from multiple sources, application profiles to enable multi-vendor policies at the hardware as well as at application layer).

Eventually, as in Fig. 2, data are fed into EEM software for analysis, and/or into other enterprise systems such as Building Management Systems (BMS), Advanced Production and Scheduling systems (APS), Manufacturing Execution Systems (MES), Manufacturing Resource Planning (MRPII), or simply into the Enterprise Resource Planning (ERP). The data from smart metering systems can also be integrated with a supervisory control and data acquisition system (SCADA).

4. Current and expected IoT-based energy management practices

The adoption of IoT technology for monitoring energy consumption on the shop floor is still at a primitive stage compared to the number of discrete manufacturing companies existing in the world. However, several manufacturing companies have installed such systems for monitoring the energy consumption at a machine level.

Relying on experts knowledge (including technology providers), the analysis of online information published by companies that have already adopted the IoT technology for monitoring energy consumption as well as on the literature review (cf. Section 2); Table 2 rationalizes which sets of benefits that have been achieved as of today (Column 1) thanks to energy management practices enhanced or enabled by such technology (Column 2). Moreover, Column 3 shows the impact of the availability of energy data on

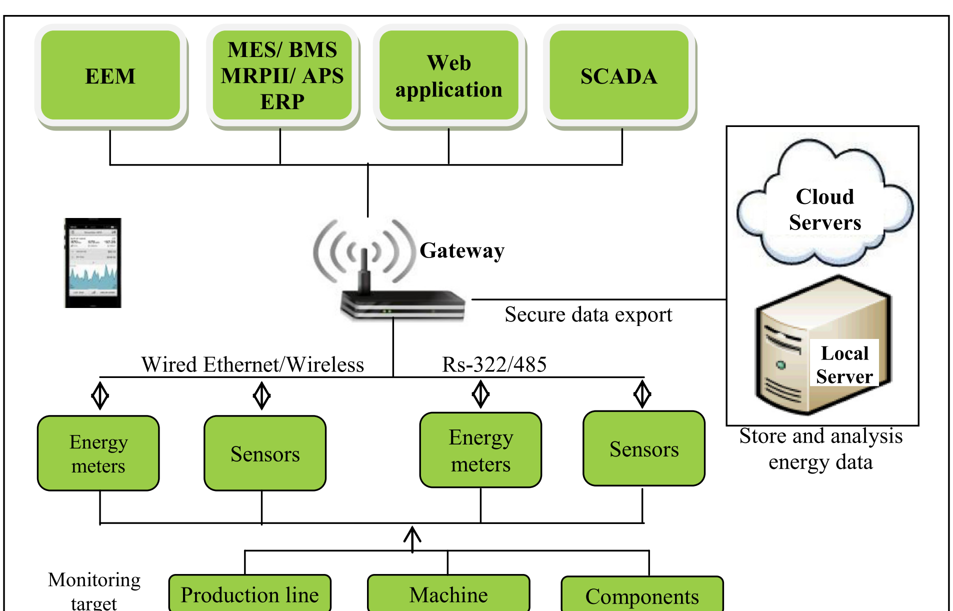

Fig. 2. General IoT system architecture for energy monitoring.

Table 2
Benefits due to IoT adoption and related practices.

Benefits of IoT (smart meters) adoption (energy efficiency-related)	Practices enhanced or enabled by IoT (smart meters) which lead to those benefits	Enhanced/Enabled	Required data	Interval time	Necessary/Supportive tools
1. Finding and reducing energy waste sources	Comparing energy consumption with production level to find the waste source.	Enabled	(6), (10)	Real-time, hourly, daily	e-KPIs, Visualization tools
	Comparing energy consumption for the same process (e.g. heating, molding) in different environments, and then improve.	Enabled	(4), (5), (6), (16)	Real-time, hourly, daily	e-KPIs, Visualization tools
2. Improving energy-aware production scheduling	Integrating energy consumption data into manufacturing systems to optimize production scheduling	Enhanced	(1), (2), (3), (4), (5), (6), (7), (8), (9), (13)	Real-time, hourly, daily	Optimization techniques, e-KPIs
	Energy efficient jobs routing, when there is sufficient machine flexibility to do so	Enhanced	(4), (5), (6), (7), (8), (9)	Real-time, hourly	Optimization techniques, e-DSS
	Defining energy consumption for a machine in different configurations (e.g. speed), and then choosing the more efficient machine configuration.	Enabled	(4), (6), (9)	Real-time, hourly, daily	Optimization techniques, e-DSS
	Reducing idle time by switching a machine off, if energy consumption in Off/On transition is less than energy waste during idle time.	Enhanced	(1), (5), (6), (7)	Real-time, hourly (transition time).	Optimization techniques, e-DSS, e-KPIs, Visualization tools
3. Reducing energy bill 3.1 Avoiding a financial penalty due to breach of the maximum consumption levels	Reducing energy consumption at peak time (e.g. load balancing)	Enhanced	(6), (13), (14), (15)	Real-time, hourly	Optimization techniques, Visualization tools
	Negotiating with energy providers and buying energy from several suppliers	Enhanced	(13), (14), (15)	Real-time, hourly, daily	Visualization tools
3.2 Reducing energy purchasing cost	Making energy purchasing decisions (i.e. determining quantity to purchase) based on real consumption data	Enhanced	(13), (14), (15)	Hourly, daily	Visualization tools
4. Efficient maintenance management 4.1 Shifting to condition-based maintenance 4.2 Increasing energy-efficient maintenance 4.3 Increasing accuracy and reliability of equipment by ensuring it is in good condition based on real-time data.	Maintenance based on energy use pattern (e.g. predictive, proactive maintenance).	Enhanced	(10), (11), (12)	Real-time, hourly	e-KPIs,Visualization tools
5. Improving environmental reputation 5.1 Meeting customers' expectations and environmental regulations 5.2 Obtaining environmental certifications (e.g. ISO 50001)	Measuring and reducing the CO_2 footprint coming from production processes, and making such data available to stockholders	Enhanced	(1), (2), (3), (4),	Hourly, daily	e-KPIs,Visualization tools
6. Supporting decentralization in decision-making at production level to increase energy efficiency.	Using several energy KPIs to evaluate energy usage in production	Enabled	(1), (2), (3), (4), (7), (9), (10), (13)	Real-time, hourly, daily	e-KPIs
	Using visual dashboards on the shop floor to enhance decentralized visual management	Enabled		Real-time, hourly	e-KPIs Visualization tools

each practice (i.e., whether it enhances or enables the practice). Column 4 indicates which data necessity be collected to the implementation of such practices, and the numbers in brackets point to a detailed description in Appendix A. The interval time for collecting such data is illustrated in Column 5, while Column 6 briefly describes the tools necessary to support the proper implementation of practices. These tools are explained in detail in Section 5. Further information about Table 2 (for instance, which companies have implemented some of the practices illustrated) are provided in Appendix B due to space limitations.

As illustrated in Table 2, we found six sets of benefits that can be achieved thanks to practices which are IoT-enhanced or -enabled. The first set of benefits is related to energy consumption reduction. In order to achieve these benefits, two practices can be considered. The first aims to point out energy waste by comparing energy consumption with production level: when a reduction in the production output is not matched by a corresponding reduction in energy usage, this must trigger energy managers to seek the waste source, and then take action to remove it. The second aims to compare energy consumption for processes (e.g. heating, molding, etc.) in different environments, and then improve the one environment with worst performances.

The second set is related to reducing energy consumption by improving energy-aware production scheduling. In order to achieve this, four practices can be considered. The first aims to consider energy consumption data from IoT in order to optimize production planning by integrating the data into available manufacturing systems (e.g. MES, MRPII). The second aims to choose energy-efficient job routing (e.g. selecting efficient machines to produce the jobs) when there is enough flexibility to do so. This means that having detailed energy consumption data for the machines enables the operation manger to select the most efficient machine to pro-duce the jobs. In order to consider several variables (e.g. due time, energy consumption, quality, fluctuation in energy prices), opti-mizing techniques can be used to help in decision-making. The third practice aims to choose the most efficient and suitable ma-chine configuration; in other words, the availability of detailed energy data for each machine at different configurations (e.g. speed) enables the operation manager to select the most efficient speed in relation to other criteria (e.g. due time, quality). The fourth aims to reduce idle time by turning the machine off. In some ma-chines, the energy consumed during idle time is relatively high compared to energy consumed during production processes and knowing the energy consumption patterns of the machines at different status (e.g. idle, processing, when turning machine on or off) enables energy-aware decision-making, such as optimizing the machine switch-off policy. Here, variable energy prices can be considered as well (as in Shrouf et al., 2014).

The third set is related to reducing energy consumption costs. In order to achieve this, three practices can be considered. The first aims to reduce energy consumption at peak time. Knowing energy con-sumption patterns in real-time enables managers (e.g. energy and production mangers) to make an efficient load balancing in relation to several criteria (e.g. production plan, priority, energy prices, etc.). The second practice, having up-to-date energy consumption pat-terns, improves negotiation position when dealing with energy providers and helps when buying energy from several suppliers. For example, the availability of energy consumption pattern at different times (e.g. hourly) enables the factory to buy energy from several suppliers based on energy prices during different periods. The third practice aims to define the amount of energy that must be purchased based on real data and production plans. Accordingly, it avoids the financial penalty that is usually incurred when agreed-upon maximum consumption level is exceeded.

The fourth set aims to improve maintenance management efficiency by identifying patterns in energy consumption. This allows maintenance decisions (e.g. repair and replacement) that avoid unwarranted increases in energy use. To do so, the impact of maintenance services needs to be evaluated (i.e. comparing energy consumption before and after maintenance); for example, a maintenance department may determine that failure to change a filter after a certain time increases energy consumption. Another practice to take proactive maintenance considers when energy consumption goes consistently out of range (i.e. when energy indicators show that equipment is going to fail).

The fifth set of benefits is concerned with the environmental effect and reputation of the factory, by measuring and reducing the CO_2 footprint of production processes (i.e. not only producing efficient products). Furthermore, having extensive energy monitoring Facilitates factories to obtain ISO 50001 certification.

The sixth set of benefits involves continuous improvement of energy efficiency at the production level by decentralizing decision-making. In order to achieve this, two practices can be considered. First, energy usage in production can be evaluated almost in real-time by using energy-key performance indicators (e-KPIs). Secondly, visual public dashboards can be installed on the shop floor to help workers and supervisors monitor energy usage in real-time and make decisions accordingly.

Further to the practices and benefits illustrated in Table 2, Table 3 presents advanced practices that may be adopted where applicable. These practices will allow management to better exploit newly acquired capabilities and attain a higher level of energy efficiency. Similar to Table 2, the practices in Table 3 have been identified through experts' judgment and literature review.

The first set of benefit in Table 3 focuses on monitoring power quality in factories. This can be achieved by monitoring energy in real-time and informing the energy provider about power oscillation occurs. Such oscillations can be deleterious in several industries; for example, glass bottles can be defective due to the vibration of production lines during a power oscillation.

The second benefit relates to cost management. Energy represents the second-largest operating cost in many industries (Davis et al., 2012). Having real-time energy data enables the precise determination of the cost of consumed energy per process, per product, per order, etc.

The third benefit is related to an increase in energy-aware process design in both the short and the long term. In order to achieve this, two practices may be considered. The first practice aims to integrate energy data into process design to reduce energy waste. The second aims to consider detailed energy data in simulations and other tools to improve expected energy consumption of the future production processes.

The fourth benefit aims to reduce energy purchasing costs by connecting to the grid. In this scenario, one could obtain energy prices from the grid (e.g., on an hourly basis), and adjust energy consumption (i.e. a demand-response approach) accordingly.

The fifth benefit is related to improving the economics of self-generated power (in the case where a factory generates power). In order to achieve this improvement, two practices can be considered. First is the efficient use of renewable energy; for example, using weather forecasting to build production schedules relying on energy that is expected to be generated and requiring energy for production (Note: SAP Company has already developed a prototype for this, and then using real-time data to adjust production based on actual generated energy (Ameling et al., 2010). The second practice aims to evaluate power generation processes; for example, comparing energy consumed in power generation processes to the value of power generated at the factory.

Table 3
Advanced benefits due to IoT adoption and related advanced practices.

New benefits of IoT (smart meters) adoption	Advance practices leading to those benefits	Enhanced/Enabled	Required data	Interval time	Necessary/Supportive tools
1. Monitoring power quality.	Reducing power oscillation from the provider.	Enabled	(15)	Real-time	Visualization tools
2. Cost management.	Calculating cost of energy consumed to produce a product/process (i.e. operational costs).	Enhanced	(4), (5), (3)	Real-time, hourly (Production time)	e-KPIs
3. Energy-aware processes design.	Integrating energy data into process design to reduce energy consumption.	Enabled	(1), (2), (3), (4), (5), (9), (18)	Real-time, Hourly, daily, weekly, monthly	eSIM-KPIs
	Using real energy data in several tools that aim to increase energy efficiency of production processes.	Enhanced	(1), (2), (3), (4), (5), (9)	Real-time, (process time)	eSIM-KPIs
4. Reducing energy purchasing costs by connecting to the grid.	Obtaining energy price information from the grid and adjusting energy consumption accordingly (i.e. demand-response approach).	Enabled	(4), (5), (6), (13)	Real-time, hourly	Visualization tools,Optimization techniques, e-DSS,
5. Improving economics of self-generated power (in the case where a factory generates power).	Using renewable energy efficiently (e.g. adjusting production schedules relying on energy that will be generated).	Enabled	(1), (4), (5), (6), (17)	Real-time, hourly	Visualization tools,Optimization techniques, e-DSS, e-KPIs
	Evaluating power generation processes.	Enabled	(13), (15), (19)	Real-time, hourly	

5. A framework for IoT-based energy management in production

In the previous section, the practices in Tables 2 and 3 can be adopted only after an energy monitoring system has been installed, and data are integrated in the company's information systems and decision making processes. Thus, the decision-makers need to know how to perform this integration. A framework for integrating measured energy data into production management process is depicted in Fig. 3, and consists of three levels.

The first level represents the monitoring and analyzing energy data phase; the data can be collected by smart meters and sensors in near real-time, and can be stored and analyzed at the factory or in the cloud. Data analysis is a significant step towards understanding the energy consumption pattern, defining the sources of waste and, eventually, transforming collected data into information. Moreover, techniques such as data mining can be used to analyze accumulated energy data to find the reasons for energy waste; the volume of such data in some factories can bring this analysis into the realm of Big Data.

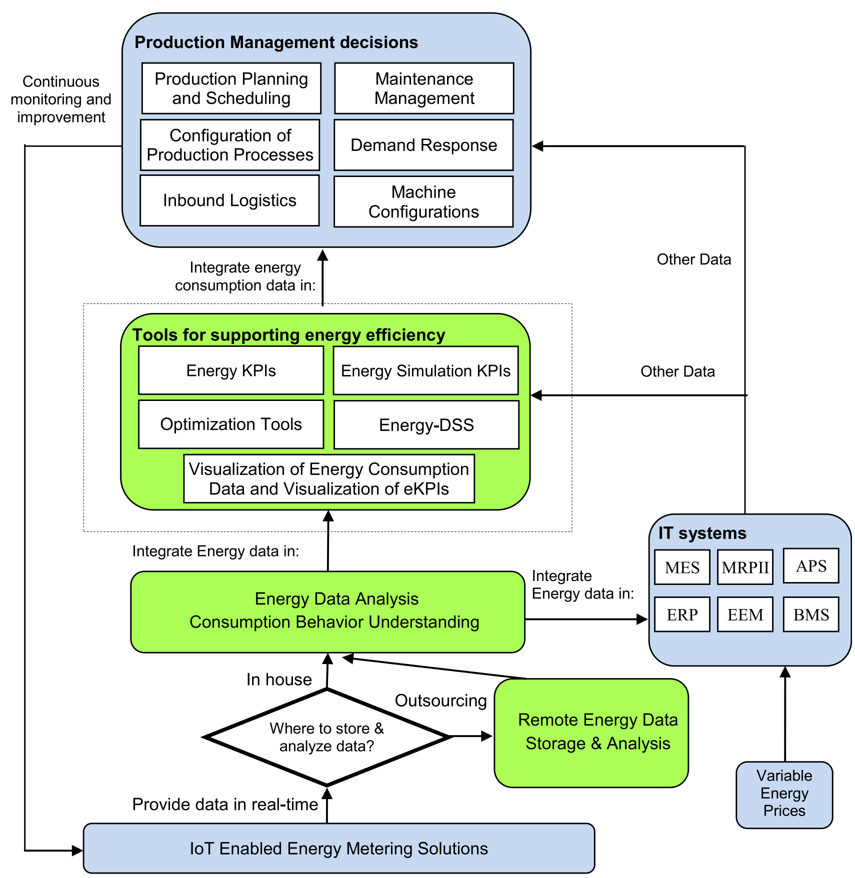

Fig. 3. Framework for IoT-based energy data integration in Production Management decisions.

The second level shows that energy related information (i.e. analyzed data) must be integrated into available production management systems and into the tools that support improving energy efficiency, such as simulation tools, optimization algorithms, energy-decision support system (e-DSS), e-KPIs, and visualization tools. Relying on information from the middle layer, the third level illustrates production management decisions that need to be adapted at the top level. Each level consists of several components, as follows.

5.1. Energy data storage and analysis

The required level of energy awareness and improvements (Miragliotta and Shrouf, 2013) are essential factors in selecting the appropriate technology (e.g. sensors, smart meters, and communication), the appropriate level of deployment (production line, machine, components, as in Fig. 2) and the appropriate data visualization/mining techniques. The collected data could be stored and analyzed locally or resorting to outsourcing (Fawkes, 2007). In such cases, energy data are stored and analyzed remotely, and the elaboration outcomes can be stored in the cloud. The output reports are sent (or published online) to the factory regularly, or instantly as in case of abnormal energy consumption.

5.2. Integrating energy data into IT systems

Energy consumption data should be integrated into MRPII/APS/MES in order to be considered in production planning, scheduling and other energy management practices. Despite the communication between the meters and the existing IT systems could be complex, two major trends have progressively made integration easier. On the one hand, sensor data from IoT meters (e.g., EpiSensor's wireless energy metering) can be sent in a variety of formats, such as CSV (comma-separated values), XML, and JSON (JavaScript Object Notation), over various protocols including FTP (File Transfer Protocol) and HTTPS (m2mnow, 2013), and more structured formats are emerging to deal with data exchange tasks. For instance, MTConnect standard (MTConnect, 2011) can be used for data collection from manufacturing equipment as in (Vijayaraghavan and Dornfeld, 2010; Vikhorev et al., 2012). This allows sources to exchange and understand each other's data and empowers software vendors to develop applications with reduced implementation issues. On the other hand, large ERP vendors are supplementing their existing systems with energy management capabilities (e.g., SAP Industrial Energy Management, Microsoft Dynamics AX/NAV). These solutions now cover meter management along with energy data monitoring, analysis, and reporting (Zampou et al., 2014). In this regard, Chofreh et al. (2014) believe that the ERP system will become central in solving the integration issues.

5.3. Tools for supporting energy efficiency

The growth in energy monitoring and management requires integration of energy consumption data in several tools to support energy-aware decision-making, such as energy efficiency KPIs (e-KPIs), visualization energy and visualization e-KPIs, energy simulation KPIs, energy-decision support system (e-DSS) and optimization tools.

Since smart meters provide detailed energy consumption data not previously available, it is important to create a set of e-KPIs so as to enhance performance evaluation. Many energy KPIs can be designed for several purposes at different levels (e.g. factory, production line, machine, and process level) as presented in (Bogdanski et al., 2012).

Visualization of energy consumption data is important too, because many workers make little effort to understand energy consumption behavior. In addition, presenting only numerical data may result in difficult interpretation of the data. Visualization of e-KPIs can also be used to help managers and workers grasp and evaluate energy efficiency continuously at different factory levels (e.g. production line, and machine level) and then make better energy-aware decision. Using visual public dashboards is an example of using visualization tools.

Energy simulation KPIs (eSIM-KPIs) is beneficial in that it provides indications of the results that might be acquired from integrating energy consumption data into management processes and modified decisions. The integration of energy data into production management decisions also requires an e-DSS to support energy-aware decision-making. Such systems provide several benefits for the factories. The first benefit is providing solutions and mechanisms to support production processes to be more energy and cost efficient. The second benefit is the rapid response to production processes needs, such as faster response to changes in energy prices (i.e. demand response).

Optimizations also play a vital role in operatively increasing energy efficiency. For example, authors have developed algorithms that minimize total weighted tardiness and total electricity consumption as (Liu et al., 2013), but precise energy consumption data are an essential input for such models and techniques. In many cases, energy data that are used in optimization problems are estimated and fixed; on the contrary, (Shrouf et al., 2014) mention the use of sensors and smart meters as tools for collecting accurate and real-time energy consumption data to be used in scheduling optimization. In this regard, the continuous monitoring of energy consumption is important not only to provide accurate data to be used in the optimization problem, but also to assure that energy consumption patterns have not changed over time, otherwise the optimization process will not provide the optimal solution.

The adoption of such tools depends on company objectives and on adopted practices (cf. Tables 2 and 3). Visualization tools and e-KPIs are necessary for most of the cited practices; conversely, for additional energy efficiency, Energy-DSS and eSIM-KPIs are required, while the use of optimization tools is indispensable for the best energy performances.

5.4. Integration energy data in production management decisions

At the higher level, the framework in Fig. 3 presents production management decisions that can be made more efficient when integrating energy data, such as production planning and scheduling, demand response, machine configuration, configuration of production processes, maintenance management, and inbound logistics.

Integrating energy consumption in production planning has been mentioned in Tables 2 and 3. The improvement in energy efficiency can be achieved by reducing idling time of the machines, non-value adding processes and by using load balancing, as extensively mentioned in literature (see for instance Herrmann and Thiede, 2009). Furthermore, shifting several production activities to low energy price periods may be a viable option, in some situations. Such practices are mostly preferred when energy consumption data are available, and when the production schedule is flexible. In this scenario, (Shrouf et al., 2014) build a mathematical model to minimize energy consumption costs for a machine schedule, by considering variable energy prices (FERC, 2012) as one of the main factor in defining the production scheduling of a machine.

In reality, machines can be configured under several speeds, and the knowledge of energy consumption pattern of each machine under different speeds enables the operations manager to select the most effective and efficient configuration. In this scenario, (Fang and Lin, 2013) consider machines' speeds in production scheduling to reduce energy consumption costs.

Understanding the energy consumption pattern of machines, ensuring the pattern is normal during the production, and finding abnormal energy consumption are ways to improve predictive maintenance. As an example, (Xiaoli et al., 2011) present an “intelligent Internet of Things for equipment maintenance” (IITEM) in order to collect both static and dynamic data of electrical and mechanical equipment by using many sensors. IITEM is able to achieve the ‘smart’ state of the equipment maintenance system and realize high-efficient energy-saving operation of the equipment in daily production.

In some cases, eco-efficient manufacturers need to re-examine the production process at a different level (Bruzzone et al., 2012). So, clear awareness of energy consumption need be considered to make efficient production processes (e.g. changing the priority of production processes) and so on. Also internal logistics can be impacted and revised thanks to energy awareness: For example, Hopf and Müller (2015) use ‘Energy Cards’ tools to determine and reduce energy demand in the logistics area.

6. Managerial recommendations and conclusions

This paper addresses a topic that decision-makers need to consider once they plan to improve the energy efficiency of their discrete-manufacturing facilities and achieve this goal thought state-of-the-art, Internet of Things solutions. These solutions, in fact, enable a very high level of awareness, being capable of being flexibly installed and collecting large quantities of energy-related data, almost in real-time. For this reason, it is important to design in advance how such IoT energy monitoring solutions have to be included in the company's energy management approach.

In this paper, relying on a literature review and on an empirical data (expert interviews, online available sources) we address this topic, which we believe is relevant for managers. Differently from traditional “solution-driven” views, this paper presents a backward approach to guide to this process: starting from the most important question (“What benefits do I want to achieve?”), the paper highlights which practices will have to be put in place; these practices require data and tools in order to be implemented and run. Along with company maturity, a set of more advanced achievable benefits and related practices are presented so that a continuous progress in energy-efficient production can be targeted.

As a second contribution, the paper illustrates what type of energy data integration architecture will have to be put in place to effectively bring the collected energy data to the low-level tools locally supporting energy efficiency up to higher-level applications which guide company manufacturing strategy. References are provided to stress the link between the key operative processes and energy related data, so as to highlight how much room there is for energy efficiency improvement once a company does not target only local efficiency gains but rather addresses this matter with the inclusion of machine configuration, advanced maintenance, production scheduling according to energy demand-response just to name a few.

The energy management practices and the proposed framework offer a novel perspective on integrating energy data into production management and related decisions at the operational level. Given the objective of this paper, an inductive approach was followed; furthermore, due to the high specificity of energy efficiency projects, no quantitative data about achieved results were considered, due to poor generalizability. This framework, therefore, needs to be tested; action research methodology appears to be the most feasible approach. On a larger scale, the energy practices collected in our search could undergo a conventional hypothesis testing (e.g. through a survey methodology) to enhance the generalizability of some of the paper's contribution. Eventually, despite being developed having in mind discrete manufacturing contexts, these contents could be refined and likely adapted to other industries, for instance continuous processing manufacturing.

Acknowledgment

This paper is produced as part of the EMJD Programme European Doctorate in Industrial Management (EDIM), which is funded by the European Commission, Erasmus Mundus Action 1.

List of acronyms

Acronyms	*Meaning*
APS	Advanced Production and Scheduling systems
BMS	Building Management Systems
CSV	Comma-Separated Values
e-DSS	Energy-decision support system
EEM	Enterprise Energy Management
e-KPIs	Energy-key performance indicator
eSIM-KPIs	energy simulation-KPIs
ERP	Enterprise Resource Planning
FTP	File Transfer Protocol
HTTP	Hypertext Transfer Protocol
IITEM	Intelligent Internet of Things for Equipment Maintenance
IoT	Internet of Things
IT	Information Technology
JSON	JavaScript Object Notation
M2M	Machine to Machine communication
MES	Manufacturing Execution Systems
MRPII	Manufacturing Resource Planning
RFId	Radio-frequency identification
SCADA	Supervisory Control and Data Acquisition System
ToU	Time of use
XML	Extensible Markup Language

Appendix A

Table A.1
Additional data needed to enable practices mentioned in Tables 2 and 3 (aside from energy consumption data).

Number	Supportive data
1.	Transition time per machine (i.e., time to switch from one status to another)
2.	Idle time of the machines
3.	Standby time of the machines
4.	Processing time per product (J_i) on machine (M_i) at speed (S_i)
5.	Production planning (e.g., operations sequence)
6.	Production schedule (quantity, time, machines, etc.)
7.	Number of shifts per day
8.	Preferable machines for each job
9.	Quality data (e.g., per product at different speeds)
10.	Maintenance information (e.g., time)
11.	Preventive maintenance plan
12.	Proactive maintenance plan
13.	Energy price per period (e.g., electricity purchasing prices per hour)
14.	Average energy consumption per hour
15.	Related information from power purchase contracts (e.g., quantity, quality)
16.	Temperature information (e.g., process, air temperature)
17.	Weather forecasting
18.	Data from machine controller (e.g., oil temperature)
19.	Cost and amount of energy generated in the factory

Appendix B

Table B.1
Empirical database: companies which implemented the practices in Table 2.

Practices enhanced or enabled by IoT (smart meters) which lead to those benefits	Factories that have implemented the practices (and the location of the company)		
	Factory	Sector	Location
Comparing energy consumption with production level to find the waste source.	Factory A	Aircraft	Getafe- Spain
	Factory B	Beverage	Guadalajara – Spain
	Factory C	Sanitary and hygienic	Toledo–Spain
	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory E	Beverage	Aranda de Duero- Spain Palma del río -Spain
	Factory F	Food processing	Four locations in Ireland and United Kingdom
	Factory G	Produces retreaded tyres for heavy goods vehicles	Devon–United Kingdom
	Factory H	Pharmaceutical	Ireland
Comparing energy consumption for the same process (e.g. heating, molding) in different environments, and then improving.	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory I	Biopharmaceutical	Colmenar Viejo – Madrid–Spain
	Factory J	Urban Water Treatment	Palencia – Spain
	Factory C	Sanitary and Hygienic	Toledo–Spain
	Factory K	Trailer manufacturing	Ireland
Integrating energy consumption data into manufacturing systems to optimize production scheduling	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory C	Sanitary and Hygienic	Toledo–Spain
Energy efficient jobs routing, when there is sufficient machine flexibility to do so	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory C	Sanitary and Hygienic	Toledo–Spain
Defining energy consumption for a machine in different configurations (e.g. speed), and then choosing the more efficient machine configuration.	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
Reducing idle time by switching a machine off, if energy consumption in Off/On transition is less than energy waste during idle time.	Factory A	Aircraft	Getafe- Spain
	Factory I	Biopharmaceutical	Colmenar Viejo – Madrid–Spain
	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory L	Precision machining of engine components	Leicester, UK
	Factory M	Electrical equipment manufacturer	Bocholt, Germany.
Reducing energy consumption at peak time (e.g. load balancing)	Factory J	Urban Water Treatment	Palencia – Spain
	Factory B	Beverage	Guadalajara – Spain
	Factory N	Medical devices (supplier of healthcare solutions)	Ireland
	Factory O	Plastics Manufacturing	Athlone – Ireland.
Negotiating with energy providers and buying energy from several suppliers	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory N	Medical devices (supplier of healthcare solutions)	Ireland
Making energy purchasing decisions (i.e. determining quantity to purchase) based on real consumption data	Several factories located in Spain (e.g. factory B, C, D)		
Maintenance based on energy use pattern (e.g. predictive, proactive maintenance).	Factory B	Beverage	Guadalajara – Spain
	Factory A	Aircraft	Getafe- Spain
	Factory N	Medical devices (supplier of healthcare solutions)	Ireland
Measuring and reducing the CO_2 footprint coming from production processes, and making such data available to stockholders	Factory A	Aircraft	Getafe- Spain
	Factory K	trailer manufacturing	Ireland
Creating new energy KPIs to evaluate energy usage in production	Factory E	Beverage	Aranda de Duero- Spain Palma del río -Spain
	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory C	Sanitary and Hygienic	Toledo–Spain
	Factory F	Food processing	Four locations in Ireland and United Kingdom
Installing visual dashboards to enhance decentralized visual management	Factory F	Food processing	Four locations in Ireland and United Kingdom
	Factory O	Plastics Manufacturing	Athlone – Ireland.

Table B.2
Empirical database: companies which implemented the practices in Table 3.

Advance practices leading to those benefits	Factories that have implemented the practices (and the location of the company)		
	Factory	Sector	Location
Reducing power oscillation from the provider.	Factory I	Biopharmaceutical	Colmenar Viejo – Madrid–Spain
Calculating cost of energy consumed to produce a product/process (i.e. operational costs).	Factory D	Automotive supplier	Burgo de Osma Soria-Spain
	Factory C	Sanitary and Hygienic	Toledo–Spain
	Factory B	Beverage	Guadalajara – Spain
	Factory F	Food processing	Four locations in Ireland and United Kingdom
Integrating energy data into process design to reduce energy consumption.	Factory C	Sanitary and Hygienic	Toledo–Spain
	Factory P	Fabrication of wind turbines	Spain
Using real energy data in several tools that aim to increase energy efficiency.	Several factories located in Spain (e.g. factory A, B, C, D)		
Obtaining energy price information from the grid and adjusting energy consumption accordingly (i.e. demand-response approach).			
Using renewable energy efficiently (e.g. adjusting production schedules relying on energy that will be generated).	SAP company has built a prototype (Ameling et al., 2010)		
Evaluating power generation processes.			

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