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Utilizing the Internet of Things to promote energy awareness and efficiency at discrete production processes: Practices and methodology

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Abstract

In today’s manufacturing scenario, rising energy prices, increasing ecological awareness, and changing consumer behaviors are driving decision makers to prioritize green manufacturing. The Internet of Things (IoT) paradigm promises to increase the visibility and awareness of energy consumption, thanks to smart sensors and smart meters at the machine and production line level. Consequently, real-time energy consumption data from the manufacturing processes can be easily collected and then analyzed, to improve energy-aware decision-making. This thesis aims to investigate how to utilize the adoption of the Internet of Things at shop floor level to increase energy-awareness and the energy efficiency of discrete production processes. In order to achieve the main research goal, the research is divided into four sub-objectives, and is accomplished during four main phases (i.e., studies).

In the first study, by relying on a comprehensive literature review and on experts’ insights, the thesis defines energy-efficient production management practices that are enhanced and enabled by IoT technology. The first study also explains the benefits that can be obtained by adopting such management practices. Furthermore, it presents a framework to support the integration of gathered energy data into a company’s information technology tools and platforms, which is done with the ultimate goal of highlighting how operational and tactical decision-making processes could leverage such data in order to improve energy efficiency.

Considering the variable energy prices in one day, along with the availability of detailed machine status energy data, the second study proposes a mathematical model to minimize energy consumption costs for single machine production scheduling during production processes. This model works by making decisions at the machine level to determine the launch times for job processing, idle time, when the machine must be shut down, “turning on” time, and “turning off” time. This model enables the operations manager to implement the least expensive production schedule during a production shift.
In the third study, the research provides a methodology to help managers implement the IoT at the production system level; it includes an analysis of current energy management and production systems at the factory, and recommends procedures for implementing the IoT to collect and analyze energy data. The methodology has been validated by a pilot study, where energy KPIs have been used to evaluate energy efficiency.

In the fourth study, the goal is to introduce a way to achieve multi-level awareness of the energy consumed during production processes. The proposed method enables discrete factories to specify energy consumption, CO₂ emissions, and the cost of the energy consumed at operation, production and order levels, while considering energy sources and fluctuations in energy prices.

The results show that energy-efficient production management practices and decisions can be enhanced and enabled by the IoT. With the outcomes of the thesis, energy managers can approach the IoT adoption in a benefit-driven way, by addressing energy management practices that are close to the maturity level of the factory, target, production type, etc. The thesis also shows that significant reductions in energy costs can be achieved by avoiding high-energy price periods in a day. Furthermore, the thesis determines the level of monitoring energy consumption (i.e., machine level), the interval time, and the level of energy data analysis, which are all important factors involved in finding opportunities to improve energy efficiency. Eventually, integrating real-time energy data with production data (when there are high levels of production process standardization data) is essential to enable factories to specify the amount and cost of energy consumed, as well as the CO₂ emitted while producing a product, providing valuable information to decision makers at the factory level as well as to consumers and regulators.
Resumen

El actual contexto de fabricación, con incrementos en los precios de la energía, una creciente preocupación medioambiental y cambios continuos en los comportamientos de los consumidores, fomenta que los responsables prioricen la fabricación respetuosa con el medioambiente. El paradigma del Internet de las Cosas (IoT) promete incrementar la visibilidad y la atención prestada al consumo de energía gracias tanto a sensores como a medidores inteligentes en los niveles de máquina y de línea de producción. En consecuencia es posible y sencillo obtener datos de consumo de energía en tiempo real proveniente de los procesos de fabricación, pero además es posible analizarlos para incrementar su importancia en la toma de decisiones. Esta tesis pretende investigar cómo utilizar la adopción del Internet de las Cosas en el nivel de planta de producción, en procesos discretos, para incrementar la capacidad de uso de la información proveniente tanto de la energía como de la eficiencia energética. Para alcanzar este objetivo general, la investigación se ha dividido en cuatro sub-objetivos y la misma se ha desarrollado a lo largo de cuatro fases principales (en adelante estudios).

El primer estudio de esta tesis, que se apoya sobre una revisión bibliográfica comprehensiva y sobre las aportaciones de expertos, define prácticas de gestión de la producción que son energéticamente eficientes y que se apoyan de un modo preeminente en la tecnología IoT. Este primer estudio también detalla los beneficios esperables al adoptar estas prácticas de gestión. Además, propugna un marco de referencia para permitir la integración de los datos que sobre el consumo energético se obtienen en el marco de las plataformas y sistemas de información de la compañía. Esto se lleva a cabo con el objetivo último de remarcar cómo estos datos pueden ser utilizados para apoyar decisiones en los niveles de procesos tanto tácticos como operativos.

Segundo, considerando los precios de la energía como variables en el mercado intradiario y la disponibilidad de información detallada sobre el estado de las máquinas desde el punto de vista de consumo energético, el segundo estudio propone un modelo matemático para minimizar los costes del consumo de energía para la programación de asignaciones de una única máquina que deba atender a varios procesos de producción. Este modelo
permite la toma de decisiones en el nivel de máquina para determinar los instantes de lanzamiento de cada trabajo de producción, los tiempos muertos, cuándo la máquina debe ser puesta en un estado de apagada, el momento adecuado para rearrancar, y para pararse, etc. Así, este modelo habilita al responsable de producción de implementar el esquema de producción menos costoso para cada turno de producción.

En el tercer estudio esta investigación proporciona una metodología para ayudar a los responsables a implementar IoT en el nivel de los sistemas productivos. Se incluye un análisis del estado en que se encuentran los sistemas de gestión de energía y de producción en la factoría, así como también se proporcionan recomendaciones sobre procedimientos para implementar IoT para capturar y analizar los datos de consumo. Esta metodología ha sido validada en un estudio piloto, donde algunos indicadores clave de rendimiento (KPIs) han sido empleados para determinar la eficiencia energética.

En el cuarto estudio el objetivo es introducir una vía para obtener visibilidad y relevancia a diferentes niveles de la energía consumida en los procesos de producción. El método propuesto permite que las factorías con procesos de producción discretos puedan determinar la energía consumida, el CO₂ emitido o el coste de la energía consumida ya sea en cualquiera de los niveles: operación, producto o la orden de fabricación completa, siempre considerando las diferentes fuentes de energía y las fluctuaciones en los precios de la misma.

Los resultados muestran que decisiones y prácticas de gestión para conseguir sistemas de producción energéticamente eficientes son posibles en virtud del Internet de las Cosas. También, con los resultados de esta tesis los responsables de la gestión energética en las compañías pueden plantearse una aproximación a la utilización del IoT desde un punto de vista de la obtención de beneficios, abordando aquellas prácticas de gestión energética que se encuentran más próximas al nivel de madurez de la factoría, a sus objetivos, al tipo de producción que desarrolla, etc. Así mismo esta tesis muestra que es posible obtener reducciones significativas de coste simplemente evitando los períodos de pico diario en el precio de la misma. Además la tesis permite identificar cómo el nivel de monitorización del consumo energético (es decir al nivel de máquina), el intervalo
temporal, y el nivel del análisis de los datos son factores determinantes a la hora de localizar oportunidades para mejorar la eficiencia energética. Adicionalmente, la integración de datos de consumo energético en tiempo real con datos de producción (cuando existen altos niveles de estandarización en los procesos productivos y sus datos) es esencial para permitir que las factorías detallen la energía efectivamente consumida, su coste y CO₂ emitido durante la producción de un producto o componente. Esto permite obtener una valiosa información a los gestores en el nivel decisor de la factoría así como a los consumidores y reguladores.
Chapter 1: Introduction

1.1 Research trends and relevance

Reducing energy consumption and CO₂ emissions has become one of the main economic, environmental and social issues for policy-makers, society in general, and for manufacturers. Despite heightened efforts in the world to use low or zero-carbon energy sources, which almost make up 45% of the growth in primary demand; today’s share of fossil fuels in primary energy demand (i.e., 82%) is exactly what it was 25 years ago. Moreover, the share of fossil fuels is expected to decrease from its current 82% to only a 76% share by 2035 (International Energy Agency 2014). This indicates the dramatic growth of energy consumption in the world. In fact, the manufacturing sector is one of the largest energy consumers (as seen in Figure 1.1), and its consumption is estimated at more than 31% of global energy consumption (EIA 2010). This points out the considerable impact that the industrial sector has on the environment by consuming natural resources (i.e., energy) and emissions (i.e., CO₂).

Unquestionably, the development of industrial sector is a major priority for governments, because it significantly contributes to the overall economic development of a country (e.g., providing jobs, promoting a better socio-economic situation, and so on). In order to minimize the negative environmental and economical impacts of high energy consumption by the industrial sector, great efforts have been made to employ green manufacturing and energy-efficient production processes. Today, energy efficient manufacturing processes offer several advantages to manufacturing companies, such as cost savings (rising and volatile energy prices notwithstanding) and a good reputation through fulfilling governmental and international environmental regulations as well as by adapting to the changes in consumer perception toward green products. Consequently, energy awareness of energy consumption and best practices that aim to reduce energy consumption during production are increasingly important to today’s manufacturing companies.
1.2 Research focus and main aims

In many factories, energy management practices at production levels suffer due to lack of awareness of energy consumption behavior. Monitoring and analyzing energy consumption at the shop floor level is the essential step toward achieving energy-efficient manufacturing systems. In fact, increasing the awareness of energy consumption is necessary for making essential changes across production processes at all shop floor levels. By collecting energy consumption data in real-time and evaluating this data, production management decisions can be made with consideration to reducing energy consumption; hence, energy efficiency can be improved and optimized.

New emerging autonomous technologies, such as the Internet of Things (IoT), are enhancing the monitoring of production processes, almost in real-time. An area where the IoT plays a major role is in the monitoring of energy consumption (Haller et al. 2009). IoT technology (i.e., smart meters and sensors) provides awareness of energy consumption patterns by collecting real-time energy consumption data. Accordingly, some factories have adopted such technologies to collect and analyze energy data to be considered in production management decisions.
Based on current available technologies, this research aims to investigate how to utilize the adoption of the IoT paradigm at the shop floor level by providing real-time energy consumption data to support production management practices and decision-making in order to increase energy awareness and efficiency at discrete manufacturing companies. This research starts by defining practices that are enhanced and enabled by adopting IoT at production level, and building a framework for integrating energy data (enabled by IoT) in production management. Then, a mathematical model is proposed, in an attempt to minimize energy consumption costs by considering changes in energy prices. Next, by utilizing the available energy consumption data, this research seeks to define a methodology for implementing IoT at the shop floor, and then to explain how to increase awareness of the energy being consumed for production processes at the operation, product, and order levels. To achieve the main aim of the research, this study is divided into four interdependent research sub-objectives, which are explained in Section 3.1.

1.3 Research Motivation

Rising energy prices, increasing ecological awareness, and changing consumer behavior are driving decision makers at factories to put green manufacturing and energy-efficient production processes at the top of their agenda and priorities in today’s manufacturing scenario. In fact, production processes at factories are strongly linked to high energy consumption and are considered as one of the main emitters of CO₂. As well, green factories need to show their stakeholders that the production processes were green, for example, defining green products (Jasti et al. 2015). These issues became an important challenge to both academics and managers. So, achieving the aims of this research is important, because factories are being forced to reduce energy consumption and adopt green manufacturing processes for reasons such as the following:

- Energy commonly represents the second largest operating cost in many industries (Davis et al. 2012). So, the potential cost savings are the most important driving force in making investment decisions to improve energy efficiency (de Groot et al. 2001).
➢ Energy prices are increasing for fossil fuels such as coal, oil, and natural gas.

➢ Governments and international bodies are imposing environmental regulations. Industrial countries are facing pressure to reduce their emissions, since this is an issue that is being enforced by international initiatives (e.g., the Kyoto Protocol). To face ecological issues, industrial countries force manufacturing plants to shift their action toward energy efficiency and more efficient processes (Kara et al. 2011).

➢ Customers are changing their purchasing behavior 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 that consume less energy when used by the customer.

➢ Today, the environmental challenges and green manufacturing are seen as competitive business opportunities, so decision makers are forced to reduce energy consumption (Seow & Rahimifard 2011).

1.4 Area of investigation

Presenting real-time energy consumption data at the production line, machine, process, and operation levels to the right person enables decision makers (i.e., mainly at the operational and tactical level) to know accurately current energy consumption patterns (i.e., clear energy consumption awareness). This supports decision-making with respect to changes in the production system, changes in energy prices, and the environmental impact (e.g., reducing wasted energy consumption, reducing CO₂ emissions), while maintaining required production capabilities.

In management science, according to the “Anthony pyramid,” the business activities and related decision making is generally classified in three levels: the strategic level, tactical level, and operational level (as seen in Figure 1.2). On the strategic level, long-term decisions are usually concerned with the market and types of products. The task to be executed on the tactical level relates to activities such as equipment acquisition, investment planning, etc., and the result of tactical tasks provides a basis for the operational level tasks, such as operational planning (Anthony 1965).
Following is an example of decision-making processes across these levels as they relate to energy management: A possible strategic goal is to save 12% energy consumption during the next year. On a tactical level, this could be put in practice by adopting a new, more efficient production line, adopting a monitoring system, etc. At the operational level, this involves choosing more efficient machines, better operation times, new practices, etc., while still maintaining the capacities needed.

In this example, clear energy consumption awareness is vital for such improvement. Thus, this research focuses on energy awareness and how the availability of real-time energy consumption data affects production management practices as well as related decisions at tactical and operational levels. This research also seeks to define how collecting and integrating such data can be utilized.

![Anthony’s Pyramid: a classification of business activities](image)

**Figure 1.2: Different levels of companies’ operations (Anthony 1965)**

1.5 Unit of analysis

Continuous process and semi-continuous process factories (e.g., chemical production, paper production), for which energy and materials represent major cost factors; the
energy efficiency (EE) of these processes has attracted significant attention in industrial and academic research for many years. However, in discrete manufacturing, this can be different; here, energy efficiency drew noticeable attention mainly during the last decade. This research is therefore mainly focused on discrete manufacturing.

The level of awareness regarding energy consumption behavior depends on the data collection level related to energy consumption, the implementation levels of energy measurement equipment in the production system, and the type of measurement devices used (i.e., sensors and meters). Figure 1.3 shows a schematic overview of different energy control loops at various levels that can be created by a decentralized approach (Verl et al. 2011). In this research, the adoption level of IoT will be considered at the production line and machine levels.

![Figure 1.3: Schematic of various energy control loops at the different levels of the facility (Verl et al. 2011)](image-url)
1.6 Research contributions to knowledge and practice

The contributions of this research to both knowledge and practice are highlighted below:

- Defining what benefits manufacturing companies can obtain by collecting and integrating real-time energy consumption data into their production management.
- Understanding energy management practices that enhance and enable benefits based on real-time energy data.
- Providing decision makers (e.g., energy managers) with a “benefits driven” approach for Internet of Things adoption, addressing those energy management practices that are more aligned with company maturity, measurable data, and available information systems and tools.
- Proposing IoT-based energy management within production.
- Providing a framework to support the integration of gathered energy data into the company’s IT tools and platforms, with the ultimate goal of highlighting how operational and tactical decision-making processes could leverage such data in order to improve energy efficiency, and therefore the competitiveness, of manufacturing companies.
- Demonstrating how much opportunity companies have for improved energy efficiency once they integrate real-time energy data into their production management. Such integration includes machine configuration, advanced maintenance, and production scheduling based on energy demand-response, just to name a few.
- Providing a mathematical model to minimize energy consumption cost at the machine level, with consideration of the fluctuations in energy prices (i.e., hourly based).
- Proposing an algorithm for the model that has the potential capability to be integrated into factory scheduling. Additionally, the high scalability of the algorithm allows running the production schedule in real-time.
- Demonstrating that by considering the fluctuations in energy prices in production scheduling, energy consumption costs can be reduced. This also has a positive
environmental impact through the reduction of energy consumption during peak periods, which increases the possibility of reducing CO₂ emissions from power generator sites.

- Providing a systematic way (i.e. methodology) to adopting IoT technology at shop floor to increase energy consumption awareness and then improve energy efficiency of production systems.

- Providing a new approach for enhanced, multi-level awareness for energy consumed in production processes at the operation, product, and order levels.

- Making it possible for factories to show their stakeholders how much CO₂ is emitted when producing the product, with consideration to energy sources.

1.7 Structure of the thesis

The thesis is divided into eight chapters. Chapter 1 introduces the research trend, focus, motivations, and contribution. Chapter 2 presents the literature review of energy management, energy monitoring, Internet of Things technology, and related works. Chapter 3 explains the research and questions as well as illustrates the research design. Chapter 4 presents the energy practices, benefits, and framework for adopting IoT, which addresses the first sub-objective by answering the first and second research questions. Chapter 5 illustrates the mathematical model for minimizing energy consumption cost with consideration to variable energy prices. It addresses the second sub-objective and answers the third research question. Chapter 6 shows how the third sub-objective can be achieved and answers the fourth research question; this involves implementing and validating the methodology for IoT at the shop floor level. Chapter 7 illustrates a way for increasing multi-level energy awareness at the product level, which addresses the fourth sub-objective and answers the fifth research question. Finally, the conclusion, managerial recommendations, and further work are presented in Chapter 8.
Chapter 2: Theoretical background

This chapter introduces state of the art for energy management and energy efficiency in manufacturing. Furthermore, the chapter presents recent research findings in terms of approaches and principles for energy management in factories, and it discusses current energy data collection methods. Finally, it introduces and expands upon the IoT paradigm with a focus on energy monitoring applications, as well introduces demand response concepts.

2.1 Energy management at factories

Manufacturing plants are facing increasing pressure to reduce their carbon footprint, driven by concerns related to energy costs and climate change. Thus, 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. The potential to reduce energy consumption can lie in increasing the energy efficiency (EE) of production processes and management approaches. A comprehensive literature review of the current state of improving energy efficiency methods and techniques in discrete parts manufacturing has been provided by Duflou et al. (2012).

Role of energy management is essential and has been expanded in industries (Abdelaziz et al. 2011). An energy management system (EMS) is not only technical, rather multidisciplinary in nature, and it combines management disciplines with engineering skills. It comprises a set of procedures aimed at improving energy efficiency (Thollander & Ottosson 2010). 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.
Considering the ISO 50001 as reference model, “Monitor, measurements and analysis” (e.g. collecting real-time data) has been identified on the top significant activities that need to be carefully execute for improving energy efficiency. In fact, without such kind of data; several energy saving strategies, objectives and targets are unlikely to be achieved. For instance, avoiding the peaks demand charges requires knowing the current energy consumption at production level almost in real-time (Vijayaraghavan & Dornfeld 2010). The integration of energy management with production management is one of the prominent issues towards enhancing green production systems (Bunse et al. 2011). Such as, the integration of energy consumption data in production planning and management (Herrmann & Thiede 2009; Bunse et al. 2011), such this integration requires clear awareness of energy consumption, as the case in (Wang et al. 2015).

The importance of measuring energy consumption at a production level can be seen from different viewpoints. Stich et al., (2012) indicate that companies put large amounts of effort into raising the energy efficiency in production systems from an “energy management organization and energy management culture” point of view. For instance, companies are turning-off machines during idle times, and they optimize their compressed-air systems. While from an “energy management system” point of view there is a huge lack of support for energy efficiency during the production planning and controlling. Also, from the sample that has been studied from Germany, Belgium, and Austria, more than 75% of the companies agree that the integration of IT-systems would help them in planning and decision-making. And almost the same percentage agree that only real-time processing of machine and operating data within the production planning and controlling leads to transparency (awareness) and competence in the field of energy management. On other hand, from strategic point of view (Stich et al. 2012), findings reveal that more than 50% of SME agree that the competence of measuring and analyzing energy data contributes toward a competitive advantage. Moreover, they mention that 62% of the companies discussed the possibilities of reducing peak loads with their suppliers, while only 5% of the companies measure kW-peaks. In the end (Stich et al. 2012) concludes that SMEs fail to meet their strategic energy efficiency targets because they lack information integration from the shop-floor to the planning levels.
2.1.1 Practices and procedures for energy efficiency in manufacturing

Many energy-saving activities that are used in manufacturing companies are presented in Liu et al. (2014). Such as Strengthen daily maintenance of production equipment for energy saving, Install monitoring devices for the statistics of internal energy use, promote eco-design and develop energy efficient products, optimize the transportation of raw materials and products for energy saving, Promote daily energy saving activities in offices: lighting, air-conditioning, etc. and Arrange internal training of employees to raise their energy saving awareness, etc. 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; Soroush 2010). Also, avoidance of energy consumption peaks by utilizing load shifting (Herrmann & Thiede 2009). There is also literature focusing on reducing energy consumption of machine tools (Avram & 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.

The growing awareness of the need to promote energy efficiency within manufacturing plants motivates researchers to define procedures to achieve that end. In this direction, Herrmann & Thiede (2009) propose a method that aims to increase energy efficiency within manufacturing, starting from the process chain level, by gaining an understanding about elements of the system such as cycle times and availability. Next, production machines need to be analyzed and accounted for with respect to all relevant energy and consumable inputs to and outputs from the machines. Also, the same needs to be done for relevant input and output variables related to technical building services. After this analysis, the historic load profile needs to be examined to understand detailed characteristics of consumption (e.g., consumption at peak hours), and this data have to be documented. And finally, the interdependencies of the machines, facility and building, production plans, and the best operating environment can be determined based on simulation.
In addition, Cannata et al., (2009) present procedures that support energy analysis and the management of energy efficient production processes in discrete manufacturing. These procedures are considered an evolution of (Devoldere et al. 2007), with a focus on near real-time control and management. For that, six steps have been defined: define the boundaries (e.g., machine, production line), identify the components, evaluate each state for each entity, measure the energy, conduct analysis, and offer reaction.

Fink, (2013) propose a multicriteria scheduling framework for energy-efficiency aware production planning, which includes four elements. The first element is the optimization of potentials and planning principles related to energy efficiency, such as reducing unnecessary idle times, identifying a tradeoff between the planning objectives (e.g., production speed and energy consumption), minimizing the peak load, and anticipating energy-efficiency aware production control strategies (e.g., machine states). The second element is production chains, which involve choosing the best alternative. For example, operations can be executed in different execution modes on alternative machines, so energy should be considered in defining production paths. The third element is priority rule-based scheduling procedures. And the fourth element is integration of new software into the existing planning process to improve energy efficiency. Therewith, (Fink 2013) mentions that to perform the optimization, additional energy consumption data for each single production operation and for each machine under each alternative execution mode is needed. The next section discusses the needs and tools for energy monitoring.

2.1.2 Energy monitoring and data collection methods

In reality, unawareness of the energy consumption resultant from lacking measurements systems (i.e., sub-metering) is highlighted as one of the main barriers to improving energy efficiency in non-energy-intensive manufacturing by Rohdin and Thollander (2006), in energy intensive industry by Trianni et al. (2013), and for small to medium enterprise by (Kostka et al. 2013). This means manufacturing machines and equipment are generally not metered permanently (Müller & Löffler 2009). Without clear awareness
of energy consumption behavior both at the production line and machines level, decisions at the production management level are not likely to be energy-efficient decisions.

This issue 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). Seow and Rahimifard, (2011) propose modeling energy consumption flow across manufacturing systems based on a product viewpoint as well as utilizing energy consumption data at the process and plant levels to present a breakdown of energy used throughout production. Behrendt et al., (2012) propose a methodology to present a detailed description based on standard assessment procedures to characterize the power demand of machining tools. The data for evaluating and optimizing the operational behavior of a machine can be generated by executing the three steps of the methodology. First, identify the highly dominant idle power, then evaluate the optimization strategies that aim to turn the machine off (i.e., reduce idle time) when not in use. Second, evaluate the effectiveness of optimization efforts regarding specific components (e.g., spindles, drives, and coolant pumps). The third step mainly addresses machine tool manufacturers regarding the overall machine tool concept.

Additionally, Liu et al. (2014) propose a methods to predict the energy consumption of the main driving system of a machine tool in a machining process. First, a machining process is divided into three periods: start-up, idle, and cutting. Second, energy consumption prediction models are established for each period and a total prediction model is established for the machining process. Third, by measuring energy consumption data of the start-up and idle processes (i.e., machine status) at discrete speeds, the functions of the fitted curves of the energy consumption during start-up and idle periods are obtained, which enables the prediction of the energy consumption of the start-up period and the idle period at any given speed. Fourth, using the cutting power calculated based on the machining parameters and the additional loss coefficients obtained based on the additional loss coefficients equation set, the energy consumption of the cutting periods can be predicted. Finally, a prediction error analysis model can be constructed.
Furthermore, (Hu et al. 2012) built an online approach for monitoring the energy use of machine tools based on an energy consumption model of machine tools (i.e., without using a torque sensor). They assume the energy consumption of machine-tools can be divided into two parts: the first is constant energy consumption, measured in advance and stored in a database, and the second is variable energy consumption which is derived from cutting power that can be estimated on-line according to power balance equation and additional load loss function. The system can acquire energy efficiency-related information of machining tools (e.g., idle time); based on this information, the energy efficiency can be enhanced in two ways. First, some management measures, such as task scheduling, can be taken to reduce idle time; the second is to take some technical measures for optimizing cutting parameters to shorten cutting time. One of the limitation of method proposed in (Hu et al. 2012) is accuracy of variable and constant energy consumption that could change later for any reason. In reality, however, energy consumption can be different from the energy that is identified in the machine’s power profile; consequently, this will effect prediction for energy consumption for any process. So, estimation of energy consumption does not necessarily reflect the real consumption and the data provided are not necessarily accurate.

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. The needs for accurate energy consumption data to understanding, assessment, and break down the energy consumption behavior within a manufacturing plant has motivated researches, and the decision maker
to invest to collect required data almost in real-time. Here, Sensor technology (Bunse & Vodicka 2010), and energy metering are considered important key technology for the assessment of current performance, and enhance energy management improvement at production system.

Actually, implementing of advanced metering infrastructure (AMI) at shop floor is one example that shows the importance of adopting ‘Internet of Things’ technology for improving energy consumption awareness at different levels of production systems, and promote energy management system. Smart meters provide innovative opportunities for improving energy management practices. Haller, Karnouskos, & Schroth, (2009) claim smart meters “will be able not only to provide ‘near’ real-time data, but also process them and take decisions based on their capabilities and collaboration with external services”.

Installing the energy measurement equipment at a factory needs to be planned; considering different factors, such targets from collecting energy consumption data at different levels of the factory. Kara et al. (2011) and O’Driscoll & O’Donnell, (2013) generally define three level of installation of these metering system. First: at factory level, meter which is typically installed between the main factory electrical incomer and utility provider. Second, Process line/ department/ process chain metering, collecting this data is helpful for considering energy consumption data in production schedules, calculate the improving of energy savings achieved after adopting an energy efficiency project, and benchmarking. Third, metering at machine level and power monitoring, this 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 technical improvements. Table 2.1 shows details of electrical metering applications (based on (Queensland Manufacturers project 2010).
<table>
<thead>
<tr>
<th>Application</th>
<th>Feature/Comments</th>
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</table>
| 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.                                                                                                                                                                                                 |

**Table 2.1: Details of electrical metering applications**

To promote energy awareness, Vikhorev et al, (2012) propose a framework for energy monitoring and management in a factory in order to help decision support systems to consider energy used by each different productive asset and the related energy processes in use. The Limitations of the proposed framework in Vikhorev et al, (2012) are the requirement for expert knowledge during training Also, that paper does not reflect quantities data to evaluate the impact that adopting such a system would have on improving some KPIs (e.g., energy efficiency, energy cost, etc.). Furthermore, Miragliotta & Shrouf (2013) propose a framework for IoT adoption to monitor the shop floor based on the factory aim, increasing energy awareness as well as improving and optimizing energy-efficiency at manufacturing.
2.2 Internet of Things

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.

2.2.1 What is IoT

According to Miragliotta, Perego & Tumino (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 tag to a maximum of a wireless network of sensors/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.

2.2.2 IoT technology and Smart meters (IoT architecture for improving Energy Efficiency)

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. General system architecture for energy monitoring in factories using Internet of Things technology can be derived, as illustrated in Figure 2.1.

![General IoT system architecture for energy monitoring](image)

Figure 2.1 General IoT system architecture for energy monitoring
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, 2006), 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 object 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 Figure 2.1, 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).
2.3 Demand response

Since changes in energy prices is a factor considered in the research (see chapter 5). This section is dedicated to explaining its concept and impact on the environment.

Energy demand-side management (DSM) includes peak-reduction and load shifting, which involves moving load from on-peak to off-peak energy tariff rates (Michaloski et al. 2011); this is an area in which energy cost reduction can be achieved, accordingly has a effect on reducing total production costs (Hasanbeigi et al. 2009).

Demand-Side Management is an umbrella term that includes energy efficiency and Demand Response (DR). A report prepared by Charles River Associates (2005) for the World Bank defines DSM as the “systematic utility and government activities designed to change the amount and/or timing of the customer’s use of electricity for the collective benefit of the society, the utility and its customers.” According to the Federal Energy Regulatory (FERC 2012), Demand Response is defined as “Changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.”

A review and classification of Demand Response (DR) programs are describe in (Shariatzadeh et al. 2015). Price-based programs (PBP), which are part of DR programs, include three different DR programs: critical peak pricing (CPP), time of use (TOU), and real-time pricing (RTP). In general, these programs are based on dynamic pricing rates in which the main goal is to flatten the demand curve by increasing prices during peak periods and reducing prices during off-peak periods (Shariatzadeh et al. 2015). TOU program prices are set in advance for a specific time period, typically not changing more often than twice a year (109th U.S. Congress 2005). “CPP has a different rate structure during a CPP event when the electricity usage rates are very high and the price information will be informed early before the event to the participants or consumers. In general, a CPP is implemented only during contingencies” (Shariatzadeh et al. 2015). For
RTP, which is also called “Hourly Pricing (HP),” consumers are generally informed about the prices on a day-ahead or hour-ahead basis.

In fact, significant efforts in DR have generated great economic and environmental benefits. In this direction, different strategies (Albadi & El-Saadany 2008) have been adopted in some countries to achieve the desired effect, such as the adoption of time-of-use pricing with large differences between on-peak and off-peak prices (Wang et al. 2010). Also, several countries have adopted variable energy prices (e.g. hourly base) that are based as illustrated in the following sub-section.

2.3.1 Variable energy prices

The energy market is highly developed in Italy and the rest of Europe. Variable energy prices seek to reduce energy consumption during peak times across the board. To minimize energy costs during production, it is essential to know exact energy prices at any given time. For example, the electricity market in Italy, which is commonly called the Italian Power Exchange, enables consumers to purchase electricity hourly and provides electricity prices a day in advance. Figure 2.2 shows hourly electricity purchasing prices for the following day, available online the day before on www.Mercatoelettrico.org. Furthermore, some researchers such as Lei and Feng, (2012) have proposed daily and hourly electricity price predictions in competitive energy markets. The differences in electricity prices from hour to hour or even shorter time frames are considered in this thesis (mainly chapter five) for minimizing energy consumption costs.
Figure 2.2: Shows an example of the hourly electricity price on a working day (GME 2013).
2.4 Gaps in the literature

Figure 2.3 below show the gap between the industrial need and the literature.

- How to adopt IoT at factories to increase energy-awareness of production.
- How to integrate production data with real-time energy data (with consideration of energy prices, energy sources) to improve energy-awareness; to what level can energy-awareness be achieved.
- How to optimize production to minimize energy consumption cost with consideration to energy variable prices.
- What the benefits from integrating real-time energy data (from IoT) are, and what practices lead to achieving these benefits.
- How to integrate energy data into production management.

Figure 2.3: Gap between industrial needs and the literature
Chapter 3: Research objectives and research design

The literature offers several definitions of research design. An explicit and straightforward definition is given by (Creswell 1994) who states that, “A research design is a detailed outline of how an investigation will take place including how data is to be collected, what instruments will be used and the means of analyzing the data.” This chapter first describes the research aim and sub-objectives, research questions, and hypothesis to provide understanding of the research aims and logic. Then, the research methodology illustrates the research process, explains how the research has been conducted, and describes data collection and analysis methods.

3.1 Research aim and objectives

This research aims to investigate how to utilize the adoption of the Internet of Things (IoT) paradigm at the shop floor level (by providing real-time energy consumption data) to increase energy awareness and efficiency at discrete manufacturing companies. To achieve the aim of the research; this study is divided into four interdependent research sub-objectives. Figure 3.1 links the four sub-objectives with research questions and shows how the objectives are integrated to achieve the overall research aim.

First research sub-objective: Understanding how the availability of real-time energy consumption data (i.e., by the IoT technology) at different levels of a production system (i.e., at the production line and machine level) impacts production management practices and related decisions to improve energy efficiency. That is, this sub-objective involves defining the benefits associated with energy-efficient production management practices that are enhanced and enabled by such data. And then, the goal is to illustrate how to integrate energy data in production management practices and decisions to increase energy efficiency – to enable business decisions for production management to be made in full knowledge of energy consumption of production processes. This sub-objective is discussed in Chapter 4.
**Second research sub-objective:** Finding how to optimize production scheduling at the machine level (single machine) to minimize energy consumption costs, taking into consideration the variable energy purchasing prices (i.e., hourly basis) and the availability of precise data (e.g., by smart meters) on the energy consumption of machine states. That is, this sub-objective is to define when a machine has to start processing, and when it has to stop without affecting lead time to reduce the effect of dynamic changing in energy prices. This sub-objective is discussed in Chapter 5.

**Third research sub-objective:** Building a methodology on how the IoT paradigm can be adopted at the manufacturing shop floor level to increase energy consumption awareness. By providing real-time energy consumption data on production processes status, energy efficiency can be improved. This sub-objective is discussed in Chapter 6.

**Fourth research sub-objective:** Illustrating how to achieve awareness of energy consumption for production processes by specifying the amount of energy consumed and CO₂ emitted as well as the cost of energy consumed at the operation, product, and order levels. This sub-objective is illustrated in Chapter 7.

For achieving the research aim and sub-objectives, the research questions in the following Section 3.2 have been investigated and answered.

### 3.2 Research questions

**RQ1:** What are energy-efficient production management practices that are enhanced and enabled by adopting innovative monitoring systems (i.e., IoT)? And what are the benefits that can be achieved through such systems?

In other words, what is the impact of having a high level of energy consumption awareness at production processes in supporting energy-efficient production management practices and decision making for improved energy efficiency? An extensive energy monitoring system helps increase energy awareness at the production systems. Accordingly, several energy-efficient production management practices can be enhanced
and enabled by IoT technology. Defining such practices helps the decision makers to understand the capabilities and benefits that can be achieved by adopting IoT to improve energy efficiency.

**RQ2: How are energy-aware production management practices supported by collecting real-time energy data from the shop floor by means of IoT technology in order to improve Energy Efficiency?**

Building a conceptual framework illustrates how to integrate real-time energy data into IT systems, tools that support the integration of energy data into production management practices and decisions.

**RQ3: How does considering variable energy prices in scheduling processes affect reducing production costs?**

A mathematical model and an optimization technique are needed to optimize production schedules. This model should consider variable energy prices in production shift so as to prove that considering this variable will affect reduction of production costs.

**RQ4: Depending on the business situation and need, how can IoT technology be adopted at the shop floor level to increase energy awareness of the production processes in order to improve energy efficiency?**

Real-time energy data that can be collected using sensors and smart metering are massive. Thus, adopting this technology for the energy monitoring of production systems requires well-planned methodology. This methodology may include collecting energy data, analyzing that data, using energy KPIs to evaluate the energy efficiency of production processes based on the real data, and then integrating energy data in production management decisions. Furthermore, the barriers facing IoT implementation should be identified (e.g., behavior such as managers not wanting to change their work pattern or a lack of knowledge of the benefits of applying such systems, technical problems, and so on).
RQ5: Based on integrating real-time energy data and production data, how can multi-level energy awareness at the operation, product, and order levels be achieved?

Integrating real-time energy data and production data make possible to calculate energy consumed, CO\textsubscript{2} emitted, and the energy costs for producing a product and an order. These need to be determined in automatic ways and with consideration to variable energy prices and the source of energy uses in production. Here, the data and tools required needs to be defined as well as how to achieve this goal.

![Figure 3.1: Link sub-research sub-objectives and research questions with main research aim](image)

3.3 The Research Hypotheses

*Proposition 1a – Available energy consumption data provided by IoT enable factories to adopt more advanced energy management methods, impacting different production management practices.*
Real-time data of energy consumption enable decision makers at tactical and operational levels the ability to adopt advanced energy management methods to gain more benefits from the collected data. Increasing energy efficiency in production processes can be achieved by many practices; through considering energy data, production management practices, and decisions such as production planning, maintenance, etc.

*Proposition 1b – The adoption of new energy management methods, as a result of data provided by IoT, improves the quality of production management practices and decision making, and hence benefits can be achieved.*

Adopting IoT technology enables and enhances production management practices, and such practices can be classified in sets, and each set leads to one or more benefits.

*Proposition 2 – Variable energy fee structures increases the complexity of the energy management task.*

Achieving clear awareness of energy consumption is the first step to improving energy efficiency, but achieving more improvement (i.e., near to optimization) in energy consumption and reducing the consumption costs are complex, especially when variable energy prices are in place. Here, energy management is required to tackle new challenges for different situations (e.g., managing the production schedule with consideration to different energy prices during different shifts).

*Proposition 3 – The Internet of Things is an important enabler for collecting data on energy consumption in real-time (thereby increasing awareness), which leads to overcoming existing barriers.*

Adopting the IoT for monitoring energy enables greater awareness of energy consumption within production processes. Such awareness is significant for improving energy efficiency at the production level. Furthermore, it helps in overcoming some of the energy efficiency barriers, such as a lack of information regarding energy efficiency opportunities, discovering inefficiencies in energy consumption, etc.
Proposition 4 – Real-time energy data with production data enable new levels of energy awareness at the product level.

Integrating Real-time energy data with production data at the operation level make specifying energy data (energy consumed, CO₂ emitted, and energy costs) possible for both product and order.
3.4 Research Methodology

This section explains how the research was carried out, which methods have been used to collect data, conduct analysis, and validate the results (e.g., the energy-efficient production management practices, framework, the mathematical model, the methodology, and multi-level energy awareness). In general, the research approach is divided into two categories: deductive and inductive approach (Saunders et al. 2007). Thus when conducting scientific research, it is necessary to define which approach is being implemented. In the deductive approach, the researcher develops a theory and hypothesis, as well designs a research strategy to test the hypothesis. In the inductive approach, the researcher would collect data and then develop a theory as a result of the data analysis. Here, the purpose would be to catch what is going on, so as to understand better the character and nature of the problem. The researcher’s task would be to analyze the collected data (Saunders et al. 2009). Table 3.1 shows the main differences between the deductive and inductive approaches:

<table>
<thead>
<tr>
<th>Deductive emphasizes</th>
<th>Inductive emphasizes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scientific principles</td>
<td>Gaining an understanding of the meanings humans attach to events</td>
</tr>
<tr>
<td>Moving from theory to data</td>
<td>A close understanding of the research context</td>
</tr>
<tr>
<td>The need to explain causal relationships between variables</td>
<td>The collection of qualitative data</td>
</tr>
<tr>
<td>The collection of quantitative data</td>
<td>A more flexible structure to permit changes of research emphasis as the research progresses</td>
</tr>
<tr>
<td>The application of controls to ensure validity of data</td>
<td>A realization that the researcher is part of the research process</td>
</tr>
<tr>
<td>The operationalization of concepts to ensure clarity of definition</td>
<td>Less concern with the need to generalize</td>
</tr>
<tr>
<td>A highly structured approach</td>
<td></td>
</tr>
<tr>
<td>Researcher independent from what is being researched</td>
<td></td>
</tr>
<tr>
<td>The necessity to select samples of sufficient size in order to generalize conclusions</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1: Major differences between deductive and inductive approaches (Saunders et al. 2007)
In general, a deductive approach was used at the starting point of this research by reviewing the literature, finding the gap, and then defining the main research aim. Then, an inductive approach was chosen as being the most appropriate to the nature of the topic and to achieve the aim of the research. So as to

- Understand the research context in a deeper manner
- Collect qualitative type data
- Include the researcher as a part of the research process
- Adopt IoT at a manufacturing company to improve energy efficiency in a real case

In order to achieve the research aim and sub-objectives, the research methodology adopted mixed methods. Given the exploratory nature of the first research sub-objective, a qualitative research approach based on semi-structured interviews and the collection of available data online was used. In order to achieve the second research sub-objective, a mathematical models and optimization technique have been used. For achieving the third sub-objective, a pilot study has been carried out in order to implement and validate the methodology for adopting IoT at the production level and gather the data through fieldwork. Then, how multi-level energy-awareness can be achieved was defined (fourth sub-objective). The following sub-section presents the research process.

### 3.4.1 Research Process

The first step in the research process as seen in Figure 3.2 was a critical review of the literature on energy-efficient manufacturing and an exploratory study (i.e., interviews with experts) to identify the gaps between theory and practice. Based on that, the research focus, unit of the analysis, research aim and sub-objectives, and research questions have been identified. In order to achieve the research sub-objectives, the research was conducted in four phases (i.e., studies), and each phase ended with the achievement of the related research sub-objective and the answers to the related research question(s). In terms of scientific publications, two journal papers in journal of cleaner production, one book chapter, one conference paper, and an abstract of a conference paper have been published.
How can factories successfully adopt the IoT paradigm in production management to improve energy efficiency

Critical review of Energy Management in Production
(EE, Monitoring, practices for EM, barriers, methodologies in EE)

Exploratory study
(Interviews with experts)

Gap in Theory and Practice

Research framework, Research focus, aim, and questions

Research aim:
Utilizing IoT for improving energy awareness efficiency at factories

First research sub-objective
Define the impact of IoT on improving EE (Practices, benefits & Framework)

Second research sub-objective
Optimize production schedule to minimize energy consumption cost

Third research sub-objective
Create a methodology for adopting IoT to improve EE at production level

Fourth research sub-objective
Increase multi-level energy awareness at operation, product, and order levels

Methodology
- Systematic Literature review
- Interviews with 10 experts (6 tech providers, 2 energy management consultants, 2 IoT experts)
- Online reports

Results
- Energy-efficient production management practices that are enabled/enhanced by adopting IoT
- Benefits from IoT adopting
- Building a framework for adopting IoT in production management to improve energy efficiency (Ch 4)
- A mathematical model for minimizing energy costs of production has been built
- An algorithm to define the energy-cost production schedules for a machine (Ch 5)
- A methodology for adopting IoT at production level
- Validation of the methodology
- Barriers of implementing it (Ch 6)
- Energy-awareness includes: energy consumed, CO₂ emitted, and cost at:
  - Operation level
  - Product level
  - Order level (Ch 7)

Figure 3.2: The research process
3.4.1.1 The first phase (i.e., study): achieving the first research sub-objective

Figure 3.3 shows the research design followed to achieve the first research sub-objective:

First, a systematic literature review of concepts and theoretical frameworks on energy management practices and the IoT paradigm was conducted. This review 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 the research in Chapter 2, 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).
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 provided insight into the current sustainable practices at manufacturing companies as well as 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 focused 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 what technology had been installed and what energy management practices were adopted after collecting and analyzing energy data, and what benefits they observed.

Finally, 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).

3.4.1.2 The second phase (i.e., study): achieving the second research sub-objective

In order to achieve the second sub-objective, a mathematical model is proposed for single machine production scheduling in order to minimize energy consumption costs during production processes by identifying the launch time for processing each job, taking into consideration the continuously changing energy prices during production shifts. To obtain an approximate set of the best alternatives for the problem, genetic algorithm
technology has been utilized. Furthermore, in order to ensure that the proposed heuristic solution provides the minimum cost as well provides the best possible schedule for minimizing energy costs, an analytical solution has also been run to generate the optimal solution.

Figure 3.4 shows an IDEF0 diagram for a production schedule of a single machine; it shows all input, output, variables and tools for solving the problem.

Figure 3.4: IDEF0 Diagram for optimizing production schedules

3.4.1.3 The third phase (i.e., study): achieving the third research sub-objective

This phase was dedicated to building, implementing, and validating the methodology for adopting IoT technology at the shop floor level. This step started with the extensive study of the literature review. Next, the real need to increase awareness related to improving energy efficiency was defined and analyzed, and how IoT could be implemented to play a main role to achieve the target was identified. At this step, the initial part of the methodology had already been developed.
Then, the methodology was implemented using a pilot study at a factory in Spain, so as to validate it. The implementation includes the analysis of production systems, definition of the practices that need real-time energy data (i.e., results of the first sub-objective), definition of the level of adopting the IoT, and where smart meters and/or sensors have to be installed to improve energy efficiency. Here, the methodology had to be revised. During the pilot study, real-time energy data from production processes was collected, analyzed, and evaluated.

Furthermore, a secondary validation for the methodology was carried out by comparing it with the methods that are used in a different case (i.e., an aircraft factory in Getafe-Spain). This other case started with interviews of energy managers, and then a tour onto the shop floor, which led to an understanding of the way energy data were collected and analyzed. The output from this case offers an understanding of how they had implemented the technology used to collect, store, and analyze the data. Moreover, the output shows the way (i.e., method) they are improving energy efficiency based on an analysis of the energy data at the factory level and at the shop floor level. This data helps to validate the methodology.

**Data Collection methods**

The different methods used for collecting the data during the pilot study were as follows:

First, observations: Data were collected from the field by visiting the shop floor during the study. To increase the reliability and accuracy of the observational evidence, observation activities were continuous during the study.

Second, documentation: The goals of using this method include collecting the explicit data as well as corroborating and supplementing evidence from further sources. So, several types of documents have been used to collect data, such as

- Production schedule for the implementation period.
- Maintenance data.
- Energy bills.
- Machine information.
- Energy prices.
- Other related data.

Most of these documents were collected directly from the companies.

Third, qualitative data: Qualitative data includes discussions (open interviews) with the general manager, operations manager, maintenance manager and technicians, quality manager, and workers at the shop floor i.e., the operator of the machines, (see Chapter 6).

Fourth, energy data: The collecting and analyzing of energy data are explained in Chapter 6.

In order to increase the benefits from collecting data from the above sources, some principles had to be considered during data collection in the study. These principles included using several sources of evidence (converging related issues on the same facts or findings), creating a database for the data collected for the study, and maintaining a chain of evidence, links among the data collected. The incorporation of these principles into the study is to increase its quality, and its reliability (Yin 2009).

3.4.1.4 The fourth phase (i.e., study): achieving the fourth research sub-objective

Besides the data that were collected in the third phase (i.e., during pilot study), the business process tool, XPDL, was used. More information related to this phase is discussed in chapter 7.
Chapter 4: Energy management based on Internet of Things: practices, achievable benefits and framework for adoption in production management decisions

4.1 Introduction

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 chapter is to understanding of energy-efficient production management practices that enhance and enable by IoT technology (i.e. integrating real-time energy consumption data into production management). As well, it discusses the benefits that can be obtained thanks to adopting such management practices. Furthermore, it presents a framework to support the integration of gathered real-time energy data into company’s IT tools and platforms, with the ultimate goal of highlighting how operational and tactical decision-making processes could leverage on such data in order to improve energy efficiency, and therefore competitiveness, of manufacturing companies.

Given these introductory remarks, the chapter is structured as follows: Based on improved energy consumption awareness, section 4.2 illustrates energy management practices that are enhanced and enabled by adopting IoT. And section 4.3 then presents a framework for energy management based on the integration of energy data coming from IoT devices.

4.2 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 (see section 3.4.1.1); Table 4.1 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 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 Table 4.3. 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 4.3. Further information about Table 4.1 (for instance, which companies have implemented some of the practices illustrated) are provided in Table 4.5 due to space limitations.
<table>
<thead>
<tr>
<th>Benefits of IoT (smart meters) adoption (energy efficiency-related)</th>
<th>Practices enhanced or enabled by IoT (smart meters) which lead to those benefits</th>
<th>Enhanced / Enabled</th>
<th>Required data</th>
<th>Interval time</th>
<th>Necessary/Supportive tools</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finding and reducing energy waste sources</td>
<td>Comparing energy consumption with production level to find the waste source.</td>
<td>Enabled</td>
<td>(6), (10)</td>
<td>Real-time, hourly, daily</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
<td></td>
<td>Comparing energy consumption for the same process (e.g. heating, molding) in different environments, and then improve.</td>
<td>Enabled</td>
<td>(4), (5), (6), (16)</td>
<td>Real-time, hourly, daily</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
<td>Improving energy-aware production scheduling</td>
<td>Integrating energy consumption data into manufacturing systems to optimize production scheduling</td>
<td>Enhanced</td>
<td>(1), (2), (3), (4), (5), (6), (7), (8), (9), (13)</td>
<td>Real-time, hourly, daily</td>
<td>Optimization techniques, e-KPIs</td>
</tr>
<tr>
<td></td>
<td>Energy efficient jobs routing, when there is sufficient machine flexibility to do so</td>
<td>Enhanced</td>
<td>(4), (5), (6), (7), (8), (9)</td>
<td>Real-time, hourly, daily</td>
<td>Optimization techniques, e-DSS</td>
</tr>
<tr>
<td></td>
<td>Defining energy consumption for a machine in different configurations (e.g. speed), and then choosing the more efficient machine configuration.</td>
<td>Enabled</td>
<td>(4), (6), (9)</td>
<td>Real-time, hourly, daily</td>
<td>Optimization techniques, e-DSS</td>
</tr>
<tr>
<td></td>
<td>Reducing idle time by switching a machine off, if energy consumption in Off/On transition is less than energy waste during idle time.</td>
<td>Enhanced</td>
<td>(1), (5), (6), (7)</td>
<td>Real-time, hourly (transition time).</td>
<td>Optimization techniques, e-DSS, e-KPIs, Visualization tools</td>
</tr>
<tr>
<td>Reducing energy bill Avoiding a financial penalty due to breach of the maximum consumption levels</td>
<td>Reducing energy consumption at peak time (e.g. load balancing)</td>
<td>Enhanced</td>
<td>(6), (13), (14), (15)</td>
<td>Real-time, hourly</td>
<td>Optimization techniques, Visualization tools</td>
</tr>
<tr>
<td>Benefit</td>
<td>Description</td>
<td>Status</td>
<td>Time</td>
<td>Tools</td>
<td></td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------------</td>
<td>---------</td>
<td>-------</td>
<td>------------------------------</td>
<td></td>
</tr>
<tr>
<td>Reducing energy purchasing cost</td>
<td>Negotiating with energy providers and buying energy from several suppliers</td>
<td>Enhanced</td>
<td>(13), (14), (15)</td>
<td>Real-time, hourly, daily</td>
<td>Visualization tools</td>
</tr>
<tr>
<td></td>
<td>Making energy purchasing decisions (i.e. determining quantity to purchase)</td>
<td>Enhanced</td>
<td>(13), (14), (15)</td>
<td>Hourly, daily</td>
<td>Visualization tools</td>
</tr>
<tr>
<td>Efficient maintenance management</td>
<td>Maintenance based on energy use pattern (e.g. predictive, proactive maintenance)</td>
<td>Enhanced</td>
<td>(10), (11), (12)</td>
<td>Real-time, hourly</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
<td>Efficient maintenance management</td>
<td>Maintenance based on energy use pattern (e.g. predictive, proactive maintenance)</td>
<td>Enhanced</td>
<td>(10), (11), (12)</td>
<td>Real-time, hourly</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
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<td>Maintenance based on energy use pattern (e.g. predictive, proactive maintenance)</td>
<td>Enhanced</td>
<td>(10), (11), (12)</td>
<td>Real-time, hourly</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
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<td>Maintenance based on energy use pattern (e.g. predictive, proactive maintenance)</td>
<td>Enhanced</td>
<td>(10), (11), (12)</td>
<td>Real-time, hourly</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
<td>Improving environmental reputation</td>
<td>Measuring and reducing the CO₂ footprint coming from production processes, and making such data available to stockholders</td>
<td>Enhanced</td>
<td>(1), (2), (3), (4), (4), (7), (9), (10), (13)</td>
<td>Real-time, hourly, daily</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
<td>Improving environmental reputation</td>
<td>Using several energy KPIs to evaluate energy usage in production</td>
<td>Enabled</td>
<td>(1), (2), (3), (4), (7), (9), (10), (13)</td>
<td>Real-time, hourly, daily</td>
<td>e-KPIs, Visualization tools</td>
</tr>
<tr>
<td>Supporting decentralization in decision-making at production level</td>
<td>Using visual dashboards on the shop floor to enhance decentralized visual management</td>
<td>Enabled</td>
<td>(1), (2), (3), (4), (7), (9), (10), (13)</td>
<td>Real-time, hourly, daily</td>
<td>e-KPIs, Visualization tools</td>
</tr>
</tbody>
</table>

Table 4.1: Benefits due to IoT adoption and related practices
As illustrated in Table 4.1, 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 manager to select the most efficient machine to produce the jobs. In order to consider several variables (e.g. due time, energy consumption, quality, fluctuation in energy prices), optimizing techniques can be used to help in decision-making. The third practice aims to choose the most efficient and suitable machine 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 machines, 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 consumption patterns in real-time enables managers (e.g. energy and production managers) 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 patterns, 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 CO₂ 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 4.1, Table 4.2 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 4.1, the practices in Table 4.2 have been identified through experts’ judgment and literature review. Further information about Table 4.2 (for instance, which companies have implemented some of the practices illustrated) are provided in table 4.5 due to space limitations.

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

Table 4.2: Advanced benefits due to IoT adoption and related advanced practices.
The first set of benefit in Table 4.2 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 product, per process, 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>
<thead>
<tr>
<th>Number</th>
<th>Supportive data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Transition time per machine (i.e., time to switch from one status to another)</td>
</tr>
<tr>
<td>2.</td>
<td>Idle time of the machines</td>
</tr>
<tr>
<td>3.</td>
<td>Standby time of the machines</td>
</tr>
<tr>
<td>4.</td>
<td>Processing time per product (Ji) on machine (Mi) at speed (Si)</td>
</tr>
<tr>
<td>5.</td>
<td>Production planning (e.g., operations sequence)</td>
</tr>
<tr>
<td>6.</td>
<td>Production schedule (quantity, time, machines, etc.)</td>
</tr>
<tr>
<td>7.</td>
<td>Number of shifts per day</td>
</tr>
<tr>
<td>8.</td>
<td>Preferable machines for each job</td>
</tr>
<tr>
<td>9.</td>
<td>Quality data (e.g., per product at different speeds)</td>
</tr>
<tr>
<td>10.</td>
<td>Maintenance information (e.g., time)</td>
</tr>
<tr>
<td>11.</td>
<td>Preventive maintenance plan</td>
</tr>
<tr>
<td>12.</td>
<td>Proactive maintenance plan</td>
</tr>
<tr>
<td>13.</td>
<td>Energy price per period (e.g., electricity purchasing prices per hour)</td>
</tr>
<tr>
<td>14.</td>
<td>Average energy consumption per hour</td>
</tr>
<tr>
<td>15.</td>
<td>Related information from power purchase contracts (e.g., quantity, quality)</td>
</tr>
<tr>
<td>16.</td>
<td>Temperature information (e.g., process, air temperature)</td>
</tr>
<tr>
<td>17.</td>
<td>Weather forecasting</td>
</tr>
<tr>
<td>18.</td>
<td>Data from machine controller (e.g., oil temperature)</td>
</tr>
<tr>
<td>19.</td>
<td>Cost and amount of energy generated in the factory</td>
</tr>
</tbody>
</table>

Table 4.3: Additional data needed to enable practices mentioned in Tables 4.1 and 4.2 (aside from energy consumption data)
<table>
<thead>
<tr>
<th>Practices enhanced or enabled by IoT (smart meters) which lead to those benefits</th>
<th>Factories that have implemented the practices (and the location of the company)</th>
</tr>
</thead>
</table>
| 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  Spain  
                             Ireland and United Kingdom  
Factory G  Produces retreaded tyres for heavy goods vehicles  Devon - United Kingdom  
Factory H  Pharmaceutical  Ireland  
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  
Factory D  Automotive supplier  Burgo de Osma Soria-Spain  
Factory C  Sanitary and Hygienic  Toledo - Spain  
Factory D  Automotive supplier  Burgo de Osma Soria-Spain  
Factory C  Sanitary and Hygienic  Toledo - Spain  
Factory D  Automotive supplier  Burgo de Osma Soria-Spain  
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  Bocholt, Germany.  |
<p>| Comparing energy consumption for the same process (e.g. heating, molding) in different environments, and then improving. |  |
| Integrating energy consumption data into manufacturing systems to optimize production scheduling |  |
| Energy efficient jobs routing, when there is sufficient machine flexibility to do so |  |
| Defining energy consumption for a machine in different configurations (e.g. speed), and then choosing the more efficient machine configuration. |  |
| Reducing idle time by switching a machine off, if energy consumption in Off/On transition is less than energy waste during idle time. |  |</p>
<table>
<thead>
<tr>
<th>Practice Description</th>
<th>Factory</th>
<th>Manufacturer</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reducing energy consumption at peak time (e.g. load balancing)</td>
<td>Factory J</td>
<td>Urban Water Treatment</td>
<td>Palencia - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory B</td>
<td>Beverage</td>
<td>Guadalajara - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory N</td>
<td>Medical devices (supplier of healthcare solutions)</td>
<td>Ireland</td>
</tr>
<tr>
<td></td>
<td>Factory O</td>
<td>Plastics Manufacturing</td>
<td>Athlone - Ireland</td>
</tr>
<tr>
<td>Negotiating with energy providers and buying energy from several suppliers</td>
<td>Factory D</td>
<td>Automotive supplier</td>
<td>Burgo de Osma Soria-Spain</td>
</tr>
<tr>
<td></td>
<td>Factory N</td>
<td>Medical devices (supplier of healthcare solutions)</td>
<td>Ireland</td>
</tr>
<tr>
<td>Making energy purchasing decisions (i.e. determining quantity to purchase) based on real consumption data</td>
<td>Several factories located in Spain (e.g. factory B, C, D)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maintenance based on energy use pattern (e.g. predictive, proactive maintenance).</td>
<td>Factory B</td>
<td>Beverage</td>
<td>Guadalajara - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory A</td>
<td>Aircraft</td>
<td>Getafe - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory N</td>
<td>Medical devices (supplier of healthcare solutions)</td>
<td>Ireland</td>
</tr>
<tr>
<td>Measuring and reducing the CO₂ footprint coming from production processes, and making such data available to stockholders</td>
<td>Factory A</td>
<td>Aircraft</td>
<td>Getafe - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory K</td>
<td>trailer manufacturing</td>
<td>Ireland</td>
</tr>
<tr>
<td>Creating new energy KPIs to evaluate energy usage in production</td>
<td>Factory E</td>
<td>Beverage</td>
<td>Aranda de Duero - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory D</td>
<td>Automotive supplier</td>
<td>Burgo de Osma Soria-Spain</td>
</tr>
<tr>
<td></td>
<td>Factory C</td>
<td>Sanitary and Hygienic</td>
<td>Toledo - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory F</td>
<td>Food processing</td>
<td>Four locations in Ireland and United Kingdom</td>
</tr>
<tr>
<td>Installing visual dashboards to enhance decentralized visual management</td>
<td>Factory F</td>
<td>Food processing</td>
<td>Four locations in Ireland and United Kingdom</td>
</tr>
<tr>
<td></td>
<td>Factory O</td>
<td>Plastics Manufacturing</td>
<td>Athlone - Ireland</td>
</tr>
</tbody>
</table>

Table 4.4: Empirical database: companies which implemented the practices in Table 4.1.
<table>
<thead>
<tr>
<th>Advance Practices leading to those benefits</th>
<th>Factories that have implemented the practices (and the location of the company)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reducing power oscillation from the provider.</td>
<td>Factory I  Biopharmaceutical  Colmenar Viejo – Madrid - Spain</td>
</tr>
<tr>
<td>Calculating cost of energy consumed to produce a product/process (i.e. operational costs).</td>
<td>Factory D  Automotive supplier  Burgo de Osma Soria-Spain</td>
</tr>
<tr>
<td></td>
<td>Factory C  Sanitary and Hygienic  Toledo - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory B  Beverage  Guadalajara - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory F  Food processing  Four locations in Ireland and United Kingdom</td>
</tr>
<tr>
<td>Integrating energy data into process design to reduce energy consumption.</td>
<td>Factory C  Sanitary and Hygienic  Toledo - Spain</td>
</tr>
<tr>
<td></td>
<td>Factory P  Fabrication of wind turbines  Spain</td>
</tr>
<tr>
<td>Using real energy data in several tools that aim to increase energy efficiency.</td>
<td>Several factories located in Spain (e.g. factory A, B, C, D)</td>
</tr>
<tr>
<td>Obtaining energy price information from the grid and adjusting energy consumption accordingly (i.e. demand-response approach).</td>
<td></td>
</tr>
<tr>
<td>Using renewable energy efficiently (e.g. adjusting production schedules relying on energy that will be generated).</td>
<td>SAP company has built a prototype (Ameling et al. 2010)</td>
</tr>
<tr>
<td>Evaluating power generation processes.</td>
<td></td>
</tr>
</tbody>
</table>

*Table 4.5: Empirical database: companies which implemented the practices in Table 4.2.*
4.3 A framework for IoT-based energy management in production

In the previous section, the practices in Table 4.1 and 4.2 can be adopted only after an energy monitoring system has been installed, and data are integrated in the company 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 Figure 4.1, 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.

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.
Figure 4.1: Framework for IoT-based energy data integration in Production Management decisions
4.3.1 Energy data Storage and Analysis

The required level of energy awareness and improvements (Miragliotta & 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 Figure 2.1) 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.

4.3.2 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 system 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.
4.3.3 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 (Sproedt et al. 2015). The integration of energy data into production management decisions also requires an e-DSS to support energy-aware decision-making such as in (Marques & Neves-Silva 2015). 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 (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 4.1 and 4.2). 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.

4.3.4 Integration energy data in production management decisions

At the higher level, the framework in Figure 4.1 presents production management decisions that can made be more efficient when integrating energy data, such as production planning and scheduling, demand response, machine configuration, configuration of production processes, maintenance management, and inbound logistic.

Integrating energy consumption in production planning has been mentioned in Tables 4.1 and 4.2. 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 logistic area.
Chapter 5: Optimizing the Production Scheduling of a Single Machine to Minimize Total Energy Consumption Costs

5.1 Introduction

The rising cost of energy is one of the important factors associated with increased production costs at manufacturing facilities, which encourages decision-makers to tackle this problem in different manners. One important step in this trend is to reduce the energy consumption costs of production systems. Considering variable energy prices during one day, this chapter proposes a mathematical model to minimize energy consumption costs for single machine production scheduling during production processes. By making decisions at machine level to determine the launch times for job processing, idle time, when the machine must be shut down, “turning on” time, and “turning off” time, this model enables the operations manager to implement the least expensive production scheduling during a production shift. This can be accomplished by reducing energy consumption during high price periods in shifts. Thus, the changes in energy prices as shown in Figure 2.2 are the key factor in the proposed model.

To obtain ‘near’ optimal solutions, genetic algorithm technology has been utilized. Furthermore, to determine whether the heuristic solution provides the minimum cost and the best possible schedule for minimizing energy costs, an analytical solution has also been run to generate the optimal solution. Next, a comparison between the analytical solution and heuristic solutions is presented; for larger problems, the heuristic solution is preferable. The results indicate that significant reductions in energy costs can be achieved by avoiding high-energy price periods. This minimization process also has a positive environmental effect by reducing energy consumption during peak periods, which increases the possibility of reducing CO₂ emissions from power generator sites.

The chapter is structured as follows: Section 5.2 provides a literature review. After the presentation of the problem definition and the mathematical models in section 5.3, section 5.4 describes the implementation of the model.
5.2 Discussion for state of the art for this problem

Improving production efficiency, minimizing makespan, reducing production costs (Hoogeveen 2005), and reducing energy consumption (Liu et al. 2013) are among the most important production scheduling problems in the job shop. Mathematical models and optimizing algorithms have been widely used for optimizing production scheduling processes. In this area, Méndez et al. (2006) have reviewed the state-of-the-art optimization methods for short-term production scheduling of batch processes. Other researchers such as Lin and Liao (2008) have used an optimal algorithm to minimize the makespan to solve the uniform parallel machine problem.

Production efficiency means producing without wasting resources. Although production efficiency is significant for economic development in factories, environmental considerations and related economic effects are essential. Thus, there has recently been growing research interest in sustainability in addition to productivity. Despeissee et al. (2012) analyzed industrial practices and environmental principles to develop a conceptual manufacturing ecosystem model as a basis on which to improve environmental performance. In addition, Heikkurinen and Bonnedahl, (2013) “proposed a new sustainability-oriented business strategy to replace the traditional stakeholder or market-oriented ones.”

Many methods and solutions have been used to solve the problems of energy waste during production processes. Operational methods have been utilized to reduce energy consumption and environmental effects. One of the most relevant studies was conducted by (Mouzon et al. 2007). They investigated the scheduling problem of a single machine to minimize total energy consumption, indicating that instead of keeping the non-bottleneck machines idle, they could be turned off until needed. Particularly, they proposed operation dispatching rules as steps to minimizing energy consumption: the machine could be shut down if the energy consumption for turning it off or on was less than the idle energy consumption. To ensure enough time to turn the machine back on before the next job began, they tried to predict the time of the beginning of the next job.
Optimization methods have also been used to improve energy efficiency; for instance Yan et al. (2005) presented a model for minimizing energy consumption and the makespan for job-shop scheduling in machine systems based on an "Energy-Saving Job-Shop Scheduling" method. These researchers developed a heuristic algorithm to identify the optimal or nearly optimal solutions for the model based on the “Tabu search mechanism”.

Furthermore Liu et al. (2008) proposed a mixed-integer nonlinear programming model for the hybrid flow shop-scheduling problem to minimize energy consumption. An improved genetic algorithm solved this efficiently. Although energy consumption was mainly considered and the makespan was a key constraint, they ignored on-peak times for energy use. They assumed the machine would not be turned off until all jobs were accomplished, which means wasting energy during changes of machine states (when the machine lies in an idle status for a long time). Some mathematical models have also been proposed for dynamic scheduling in flexible manufacturing systems (FMS) with energy consumption minimization (Zhang et al. 2012), which depends on a rescheduling strategy that is triggered when a new job arrives. However, the researchers ignored the amount of energy consumption used during peak times. Yi et al. (2012) proposed an emission-aware multi-machine job shop-scheduling model for minimizing both carbon emissions and makespan; they used a multi-objective genetic algorithm to solve the optimization problem. They, too, considered only power consumption during processing and idle times, and they neglected to consider on-peak periods.

Fernandez et al., (2013) present a “Just-for-Peak” buffer inventory methodology to reduce power demand during peak periods for manufacturing systems without sacrificing system throughput. Nonlinear Integer Programming formulation has been used to establish the mathematical model. They said the “corresponding upstream machines” can be turned off during the peak periods by utilizing the buffer inventory methodology to maintain the production without being influenced; here, the transition energy between ‘ON’ state and ‘OFF’ states of machine has been ignored; whereas in reality this
assumption is not always true, several machines require significant time to turn on, so this transition should not be ignored.

Focusing on single-machine scheduling, (Yildirim & Mouzon 2011) proposed a mathematical model to reduce total completion time and minimize the energy consumption of a single machine; they used a multi-objective genetic algorithm to generate an approximate set of non-dominated solutions without considering energy consumption costs during on-peak or off-peak hours, which have been considered in this chapter.

Avoiding peak times has become an important factor in reducing energy costs. Gupta and Venkataraman (2013) developed a framework to assess strategies for optimally shifting peak load electricity consumption using distributed storage systems. The objective is to reduce the price risk because of fluctuating demand for electricity. Pechmann and Schöler (2011) claimed that unused potential for increasing energy efficiency can be identified by optimizing the production schedule; these researchers developed production planning and controlling software to support production schedules and avoid energy demands during peak hours. Their research only required knowing how much energy is used at each given time during production of a piece without considering the price during on-peak periods; they tried to create a balance in an energy consumption profile (i.e., balance loading).

Fang et al. (2011) proposed a general multi-objective mixed integer linear programming formulation for optimizing a production schedule that minimized makespan, energy (i.e., peak time total power consumption), and the carbon footprint; they considered operation speed as an independent variable to affect peak load as well as energy consumption without considering the actual time that energy was being used or the energy price during operation. Furthermore, Bruzzone et al. (2012) proposed the integration of an energy-aware scheduling module with an “advanced planning and scheduling” system. The model modifies the original timetable to reduce the shop floor power peak while “accepting possible worsening of the scheduling objectives”. The model was defined without considering the variable energy prices at on/off-peak periods.
Sun and Li (2013) established an analytical model to identify optimal energy control and estimate the potential capacity of power demand reduction based on real-time information of typical manufacturing systems during the period of a demand response event without compromising system production. Accordingly, this facilitates the reduction of overall energy costs during peak consumption periods.

Whereas the optimization of single machine is the target of this chapter, some authors have considered variable energy prices in continuous processing. Castro et al. (2009) addressed the scheduling of continuous plants, focusing on the modeling of discrete events that occur at a predefined time with a continuous time scheduling formulation. Mitra et al. (2012) provided an MILP model for optimal operational production planning for power-intensive processes in continuous manufacturing. Such a model utilizes non-dispatchable demand response programs by allowing transitions between operating modes using a discrete time representation. Additionally, scheduling problems in the steelmaking process in the context of variable electricity prices were investigated by Tan et al. (2013). The problem was solved in two phases. In the first phase, without considering variable electricity prices, a mathematical program was developed to minimize the maximum completion time for each cast. In the second phase, based on obtained relative schedules of all casts, a mathematical model was utilized to minimize the energy costs for all scheduled castings.

Focusing on avoiding peak times and considering variable energy prices, Luo et al. (2013) addressed a new ant colony optimization to solve hybrid flow shop scheduling by considering production-efficient electricity consumption. They proposed a multi-objective solution for minimizing the makespan and energy consumption power with time-of-use prices. “A list schedule algorithm is applied to construct the sequence by artificial ants and generate a complete schedule;” then a correct shift procedure is used to adjust the start time of operations aimed at minimizing the electric price cost for the schedule. They assumed that electricity prices for each period (e.g., 6, 9 hours) did not change, indicating a better solution could be found over a long period for a fixed electricity price; however, changes electricity prices in short periods, for instance, every
hour, must be considered. Moreover, they posited that electrical power consumption comprises only two parts; the electricity consumption cost of processing machines and the cost of all machines on standby. Thus, they neglected to consider the energy consumption costs of turning machines on/off, which can be significant especially when the machines must be turned on/off more than once to save energy rather than remaining idle for a certain time as suggested by Mouzon et al. (2007).

Kuster et al. (2013) use evolutionary algorithms and multi-agent technology to reconfigure production schedule, to reduce energy costs through utilizing periods with low energy prices. This requires shifting energy consuming parts of the process; since production processes often comprise of interconnected sub-processes, shifting part of the processes most probability requires other parts of the process to be shifted, thus they have rearranged the individual processing steps to make the best use of times of cheap energy. This approach is only feasible to be used when the production process are not at full capacities. As well, it requires a storage space for intermediate products, which is could be unavailable, and extra costs for related activates could be incurred. Moreover, it is not clear if the machines will be idle or turned off during periods of high energy prices.

Moon et al. (2013) proposed a model to optimize the weighted sum of two criteria: the minimization of the makespan and the minimization of time-dependent electricity costs. In their model, idling time is allowed with no electricity costs so that their solution depends on inserting idle times when energy costs are high. In addition, the cost is ranked at only three different periods (peak-load, mid-load, and off-peak-load) with three probabilities of selection. The disadvantage of the proposed ‘hybrid inserted genetic algorithm’ is the computation time.

Although many researchers have addressed energy consumption in scheduling, some of them have tried to consider energy prices during production. None of this research has addressed the scheduling problem to minimize production costs considering fluctuating energy prices over short periods (every half hour/ hour as illustrated in section 2.3.1).
5.3 Problem definition

The continuous changes in energy prices have become an important factor in defining energy consumption costs. Thus, the new production-scheduling scheme in this chapter enables operations managers to minimize the total costs of energy consumption for single-machine scheduling; this chapter considers the continuous changes in energy prices to be the main factor in the scheduling problems at machine level without extending the usual factory shift duration.

The outputs of the proposed model are to

1) Decide when to start processing every job,
2) Decide when the machine should be idle or shut down and define the transition times,
3) Provide the exact costs of energy consumption for the machine.

In reality, each machine type has different operating states and transitions that show different energy consumption patterns that can be identified by their power profiles (Weinert et al. 2011). Accurate information regarding a machine’s energy consumption can be measured using sensors or smart meters (O’Driscoll & O’Donnell 2013).

To solve the problem of minimizing energy costs, three machine states have been identified, ‘processing’ (i.e., productive), ‘idle’ (i.e., working but non-productive), and ‘shut down’. The conceptual model for the operations of this machine can be observed in Figure 5.1 Graph notation $\left(\frac{a}{b}\right)$ indicates a status or a transition requiring $a$ time units with an energy consumption of $b$ units.

Two transition times and their energy costs must be considered in this model; the elapsed time when switching from shut down to processing (i.e., turning on) and the reverse (i.e., turning off). The transitions between idle and shutdown are not considered in the model because when the machine is switching from processing to shutdown, there are two alternatives. First, the machine can switch from processing to idle for a given period of time and then switch to shutdown. The second option is to switch directly to shutdown. The first option is more costly; therefore, it is not preferred, and the same is true for
switching from shutdown to processing. In addition, the transition time between idle and processing is neglected in the model because in reality this time is too short to affect the solution.

Because each machine has a different setup time and because the times required for processing the jobs are different, the shift duration is divided into a number of segments of equal length (later called periods) to solve the minimization problem. Thus, the time for each status is defined by a number of periods, and the same is true for transitions and jobs.

![Figure 5.1: A schema for machine states and transition.](image)

5.3.1 Assumptions and constraints considered in the model.

A number of jobs are to be processed by the machine, one at a time, and pre-emption is not allowed. The processing sequence is presented, and job processing cannot overlap; once job processing has begun, it cannot be interrupted. When the machine is in a processing status, a fixed number of periods will elapse until the machine is actually shut
down (i.e., turned off). This process cannot be reversed once started and cannot last longer than a fixed number of periods. Likewise, when the machine is shut down, a different fixed number of periods will elapse until it is actually ready to process a job (i.e., turned on). This process cannot be reversed once it has started and cannot last longer than a fixed number of periods.

In the model, when the machine remains idle for a period of time, it must be turned off if the following two conditions are met: First, the time required for turning off/on the machine must be less than the idle time. Second, the energy consumption cost to turn the machine off/on must be less than the energy consumption cost during the idle status. If these two conditions are not met, the idle cost will be calculated (i.e. the machine remains idle); otherwise, the energy consumption cost to turn the machine off/on will be calculated.

The following information is required as input for the model to minimize the energy costs of machine production.

1. The duration of the production shift, which should have been defined in the production plan.
2. Energy prices during the shift (i.e., price/period).
3. Number and order of jobs and the processing time for each job (time in period).
4. Amount of power consumption per period at every machine status (e.g., processing, idle) and transactions (e.g., turning on/turning off).
5. Time required for identifying transition (e.g., turning on/turning off) in time periods.

5.3.2 Mathematical model

In this section the mathematical model is used to solve the problem described above: First, the necessary sets, parameters and variables are introduced; then the model itself is presented (constraints and objective function).
**Notation**

Sets

\( \mathcal{J} \) : Total number of jobs to be processed by the machine.

\( \mathcal{P} \) : All periods

\( \mathcal{S} \) : All states

For the sake of conciseness, the three possible states will be referred to as integer numbers: 1-processing, 2-shutdown, 3-idle.

Parameters

\( E^S_s \) : Amount of energy consumption during every period the machine is in status \( s \in \mathcal{S} \).

\( E^{T}_{ss'} \) : Amount of energy consumption corresponding to every period in which the machine is transiting from status \( s \in \mathcal{S} \) to status \( s' \in \mathcal{S} \).

\( C_p \) : Energy price corresponding to period \( p \in \mathcal{P} \).

\( T^l_j \) : Processing time (in number of periods) for \( p \in \mathcal{P} \).

\( T^{T}_{ss'} \) : Number of periods that must elapse when machine switches from status \( s \in \mathcal{S} \) to status \( s' \in \mathcal{S} \). If 0, it indicates that the machine can be in status \( s \in \mathcal{S} \) during period \( p \in \mathcal{P} \) and in status \( s' \in \mathcal{S} \) in period \( p + 1 \). If -1, it indicates that the machine cannot transit from \( s \in \mathcal{S} \) to status \( s' \in \mathcal{S} \) unless another status is included between them.

\[ \alpha_{sp} = \begin{cases} 1 & \text{if machine is in status } s \in \mathcal{S} \text{ during period } p \in \mathcal{P} \\ 0 & \text{otherwise} \end{cases} \]

\[ \beta_{ss'p} = \begin{cases} 1 & \text{if machine is in transition from status } s \in \mathcal{S} \text{ to status } s' \in \mathcal{S} \text{ during period } p \in \mathcal{P} \\ 0 & \text{otherwise} \end{cases} \]

\[ x_{jp} = \begin{cases} 1 & \text{if job } j \in \mathcal{J} \text{ is processed during period } p \in \mathcal{P} \\ 0 & \text{otherwise} \end{cases} \]

\[ s_p = \begin{cases} 1 & \text{if job } j \in \mathcal{J} \text{ is begins to be processed in period } p \in \mathcal{P} \\ 0 & \text{otherwise} \end{cases} \]
The problem can be formulated as follows

\[
\begin{align*}
\min \ & \sum_{p \in \mathcal{P}} C_p \left( \sum_{s \in S} E_s^s \alpha_{sp} + \sum_{s' \in S} \sum_{s \in S} E_{ss'}^T \beta_{ss'} \right) \\
\text{s. t.:} & \\
\sum_{j \in J} x_{jp} = \alpha_{1p} & \quad p \in \mathcal{P} \\
\sum_{s \in S} \alpha_{sp} + \sum_{s \in S} \beta_{ss'} = 1 & \quad p \in \mathcal{P} \\
\alpha_{sp} \leq \sum_{s' \in S} \alpha_{sp^+} + \sum_{s' \in S} \beta_{ss'} & \quad p \in \mathcal{P}, p \neq \text{card}(\mathcal{P}), s \in S \\
\beta_{ss'} \leq \beta_{ss'}^{p+1} + \alpha_{sp^+} & \quad p \in \mathcal{P}, s \in S, s' \in S, \beta_{ss'}^{p+1} \geq 1 \\
\beta_{ss'} \geq (\alpha_{sp} + \beta_{ss'}^{p+1} - 1)T_{ss'} & \quad p \in \mathcal{P}, s \in S, s' \in S, T_{ss'} \geq 1 \\
\beta_{ss'} + \beta_{ss'}^{p+1} \leq 1 & \quad p \in \mathcal{P}, s \in S, s' \in S, T_{ss'} \geq 1 \\
\sum_{j \in J} x_{jp} \leq 1 & \quad p \in \mathcal{P} \\
\sum_{p \leq p'} s_{j'p'} \leq \sum_{p \leq p'} s_{jp} & \quad j, j' \in J, j' > j, p \in \mathcal{P} \\
\sum_{p \leq p'} x_{j'p'} \geq T_{j} \sum_{p \leq p'} s_{jp} & \quad j \in J, p \in \mathcal{P} \\
\sum_{p \in \mathcal{P}} x_{jp} \leq T_j^l & \quad j \in J
\end{align*}
\]
\[ \sum_{p \in P} s_{jp} = 1 \quad j \in J \]  
(12)

\[ \alpha_{2p} = 1 \quad p = \{1, \text{card}(P)\} \]  
(13)

\[ \alpha_{sp} \in \{0,1\} \quad p \in P, \quad s \in S \]  
(14)

\[ \beta_{ss'} \in \{0,1\} \quad p \in P, s \in S, s' \in P \]  
(15)

\[ x_{jp} \in \{0,1\} \quad j \in J, p \in P \]  
(16)

\[ s_{jp} \in \{0,1\} \]  
(17)

Equation 1, corresponding to the objective function, computes the associated costs depending on the machine status and the energy prices in every period. Equation 2 ensures that if the machine is processing a job, the machine must be turned on. Equation 3 requires that the machine must either be in one of the states or in a transition between two states. Equation 4 and equation 5 limit the status or transition in which the machine can operate in one period if in the previous period it has been operating in a given status or transition. Equation 6 and equation 7 establish lower and upper parameters of the number of periods that the machine can operate in a transition so that an operation lasts exactly a set number of periods. Equation 8 only allows one job to be processed during each period. Equation 9 ensures that jobs are processed according to the given sequence. Equation 10 guarantees the non-preemption of jobs. Equation 11 imposes the processing time for every job. Equation 12 forces all jobs to be processed during the time limitations. Equation 13 describes the boundary conditions.

5.4 Implementation (Metaheuristics for solving the problem)

Because the shop floor scheduling problem is considered to be an NP (Non-deterministic Polynomial time) hard-complete problem (Garey & Johnson 1979), the formulated problem in section 5.3 cannot be solved in real life using analytical algorithms such as
integer programming in a useful time frame. To identify a valid solving procedure, metaheuristics techniques may be considered. In particular, genetic algorithms can help in this particular problem.

Genetic algorithms have been investigated widely in the literature. Goldberg, (1989) provided the fundamentals for genetic algorithms. Moreover, Sivanandam and Deepa (2007) have discussed the concepts of genetic algorithms in detail including pertinent information for understanding the optimization process and explanations for the various operators involved in genetic algorithms. According to the bibliography, it is necessary to establish several concepts such as gene, phenotype and population as well as operating parameters (crossover and mutation strategies and evolving configuration) to define the solution procedure completely.

In this particular problem, the sequence of jobs is fixed for this machine because the jobs are established as components of the global production schedule for the factory. The problematic decision is related to the non-operation periods between jobs. Indeed it must be decided which strategy is to be adopted in non-production periods, whether the transition to shut down is to be considered or whether the transition to the idle option is preferred. The decision is made according to the cost involved.

Thus, because the basic element to be modeled is the number of non-operating periods established between jobs, the gene is represented by an integer belonging to the interval \([0,T]\) in which \(T\) is the maximum number of time periods available if all the jobs are packaged together and considering the time required for the “turning on” and “turning off” of the total established operating periods.

The size of the population considered was 16,000 individuals, and different numbers of evolving generations were considered from 2,000 to 10,000. The elitism factor between generations was fixed at 30%, which indicates that 30% of the individuals with the best fit were retained from one generation to the next. Each individual owns a phenotype which is a collection of \(N\)-genes if the total number of jobs to be scheduled on the machine in one shift is \(N\). The cost function is the one explained in the problem

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formulation, and it will consider the best strategy during any non-working period in accordance with the cost of the energy during this period.

To render the reproduction of the study for any interested researcher easier, recombination was chosen as a polynomial crossover type. Mutation rate was established at 15%. The cross rate of phenotypes was fixed at 60%. The pseudocode for the developed algorithm is shown below.

```
Input : Parameters,
       Coding for Genes and phenotypes
       Size α of population,
       Rate β of elitism,
       Rate γ of mutation,
       Number δ of iterations

Output: Potential Solution S (best fitted individual of the population at iteration δ )

Algorithm:
// Initialization
generate α individuals randomly and save them in the population
For i =1 to α do
if the individual I is not feasible
    update the individual I with a feasible one by repairing its genes;
endif
endfor
// Assessing
Check the population’s score according to the established cost function;

// Loop until the terminal condition
For i=1 to δ do
// Elitism based selection
    number of individuals retained because of elitism n = α * β;
    select the best n individuals in the original population (iteration i) and save them into the candidate population for iteration i
// Complete the candidate
    Update candidate population for iteration i with α – n individuals;
    For j =n+1 to α do
```
if the individual j is not feasible
    update the individual j with a feasible one by repairing its genes;
endif
dendfor
// Crossover

number of crossover operations \( nc=(\alpha-n)/2 \);
for \( j=1 \) to \( nc \) do
    randomly select two individuals \( S_A \) and \( S_B \) from the population;
genenerate \( S_C \) and \( S_D \) by polynomial crossover to \( S_A \) and \( S_B \);
    if \( S_{(C,D)} \) is not feasible
        update \( S_{(C,D)} \) with a feasible one by repairing its genes;
    endif
    save \( S_C \) and \( S_D \) to the candidate population for iteration i;
endfor
// Mutation

For \( j=1 \) to \( \alpha \) do
    select an individual \( S_j \) from the candidate population for iteration i;
    mutate each \( S_j \) under rate \( \gamma \) and generate a new individual \( S^*_{j} \);
    if \( S^*_{j} \) is not feasible
        update \( S^*_{j} \) with a feasible one by repairing its genes;
    endif
    save \( S^*_{j} \) to the candidate population for iteration (i+1);
endfor
// Assessing

Check the score for the population at iteration i according to the established cost function;
dendfor
// Returning the best fitted individual in population at iteration \( \delta \)
return the best individual in the population;

In terms of software used, the C++ environment was utilized for implementation. In particular, the Sferesv2 C++ framework (Mouret & Doncieux 2010) was used for coding the problem to decrease the time required for interpretation. We have extended the gene types available in the library to consider a subset of integers and to consider the
feasibility of using the phenotype during its generation because both characteristics that were required by our problem are of standard functionality.

The analytical solution for solving the problem in specific cases has also been run in which the size of the problem enables assessment of the quality of the solution found by the GA. Next, we compared the results from the heuristic solutions with the results from the analytical solution in term of accuracy and computation time. To implement an analytical solution, AIMMS 3.13 was used as a modeler, and Gurobi was the solver.

5.4.1 Performance assessment

To assess the capability of providing a convenient decision-making tool, 13 cases were analyzed to test the completeness, reliability and scalability of the solution using several criteria such as different shift durations, various types of jobs and their numbers, and changeable energy prices. Four cases focused on the completeness and the reliability of the solution; the results for these four cases are plotted below.

The machine setup data for all the cases in this study are identical. Table 5.1 shows the machine's power consumption in the KW of each status and the transition. Table 5.2 shows the number of periods of time required to switch between the machine’s states (i.e., transition time). The energy price for each period in each case (1, 2, 3, and 4) is shown in Figures 5.2, .3, 5.4, and 5.5 in cents/KWh.

<table>
<thead>
<tr>
<th>Status and Transitions</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing status</td>
<td>4 KW</td>
</tr>
<tr>
<td>Idle status</td>
<td>2 KW</td>
</tr>
<tr>
<td>Turning on (switch from shutdown to processing)</td>
<td>5 KW</td>
</tr>
<tr>
<td>Turning off (switch from processing to shutdown)</td>
<td>1 KW</td>
</tr>
</tbody>
</table>

Table 5.1: Energy consumption profile for a machine.
### Transition Time Required to Switch Between the Machine States

<table>
<thead>
<tr>
<th>Transition</th>
<th>Number of Periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turning on (switch from shutdown to processing)</td>
<td>2</td>
</tr>
<tr>
<td>Turning off (switch from processing to shutdown)</td>
<td>1</td>
</tr>
</tbody>
</table>

*Table 5.2: Transition time required to switch between the machine states.*

### Case 1

In Case 1, there are five jobs requiring processing, and the time required for processing each job is shown in Table 5.3. The shift is divided into 32 periods, and the energy prices change many times during the shift as shown in Figure 5.2. In real life, energy prices are more expensive in the morning and afternoon. Thus, this case seeks to test whether the GA solution provides the proper strategy to minimize energy costs, for example, by avoiding processing the jobs in the morning and at other peak times.

#### Jobs

<table>
<thead>
<tr>
<th>Jobs</th>
<th>J01</th>
<th>J02</th>
<th>J03</th>
<th>J04</th>
<th>J05</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing time (in periods)</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

*Table 5.3: Shows jobs’ duration in 1st case.*

#### Figure 5.2: Shows the energy prices during the various periods and the optimal schedule for the 1st case.

The production schedule in Figure 5.2 shows that different strategies have been adopted. Thus, the machine will remain in shutdown status for the first three periods (i.e., P1, P2, and P3) because the energy prices during these periods are high. The "turning on" transition requires two periods (P4 and P5); then after processing the first three jobs, the machine will stop processing for six periods (i.e., P15, P16, P17, P18, P19, P20). There is enough room to turn off/on the machine because that process requires 3 periods and the
cost of turning it off/on is less than allowing it to remain idle. Thus, the machine will be
switched to shutdown status and begin processing jobs again at period 21 (this indicates
that the machine will be in “turning on” transition during periods 19 and 20). After
processing the last job, the machine begins “turning off” to switch to shutdown mode.

4.1.2 Case 2

In cases 2, 3 and 4, there are ten jobs requiring processing; the time for processing them
is provided in Table 5.4, and the shift is divided into 48 periods. These cases propose to
test the ability of the system to provide different schedules for the identical number of
jobs and shift durations; only the energy prices will be changed.

<table>
<thead>
<tr>
<th>Jobs</th>
<th>J01</th>
<th>J02</th>
<th>J03</th>
<th>J04</th>
<th>J05</th>
<th>J06</th>
<th>J07</th>
<th>J08</th>
<th>J09</th>
<th>J10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing time (in periods)</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 5.4: Shows job duration in 2nd, 3rd, and 4th cases.

The above G-chart in Figure 5.3 shows that the machine begins “turning on” at period 1
and begins processing at period 3. After processing the 2nd job, production processing
stops for 6 periods. Because there is enough space to turn the machine off/on and the
energy cost of these transitions is less than allowing the machine to remain in idle status,
the machine will switch to shutdown status. The machine will be in “turning off”
transition during period 8, will remain in shutdown status for three periods (P9, P10, and
P11), and will utilize periods 12 and 13 for “turning on” the machine. The identical
process will be implemented after processing the 3rd job.
4.1.3 Case 3

The production schedule in Figure 5.4 shows that the machine will begin “turning on” in period 1 and then begin processing; idle status will occur only in periods 11 and 23.

4.1.4 Case 4

The G-chart in Figure 5.5 shows that the machine begins “turning on” in the 1st period and begins processing in period 3. Job processing will be suspended for 4 periods (P22, P23, P24, and P25). Although there is enough space to turn the machine off/on, the energy cost of these transitions is greater than allowing the machine to remain idle; thus, the decision is for the machine to remain idle during these periods. Next, at period 26, the machine will restart job processing.

The above cases show that the variables in energy prices during the production shift play significant roles in defining the production schedule. In addition, the model provides proper solutions to avoid the high price periods, thus minimizing energy costs.
5.4.2 Computation time

Although the model seeks to minimize energy consumption costs for machine production, the computation time for running the solution is also an important issue. Because in real life the model could be running during working hours, the results would be achieved quickly and accurately. Thus, a comparison between the GA and an analytical solution is required to validate the reliability and scalability of both solutions.

In table 5.5, the required time for solving the problems is presented both for the genetic algorithm technique used as well as for the analytical solution of the problem. The computation time for the analytical solution depends on different factors such as the number of periods in the shift and the number of jobs to be scheduled on the machine. In addition to that, the size of the population is another factor in GA.

The results show that the computation time for GA is low and stable, and indicates the number of jobs, periods, and size of the population have little effect, whereas an increase in the number of jobs and periods has a huge effect on the computation time for the analytical solution. Thus, for larger problems, the heuristic solution is the only possible approach.

<table>
<thead>
<tr>
<th>Case A</th>
<th>Case B</th>
<th>Case C</th>
<th>Case D</th>
<th>Case E</th>
<th>Case F</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 Jobs</td>
<td>10 Jobs</td>
<td>15 Jobs</td>
<td>30 Jobs</td>
<td>45 Jobs</td>
<td>60 Jobs</td>
</tr>
<tr>
<td>32 Periods</td>
<td>48 Periods</td>
<td>80 Periods</td>
<td>95 Periods</td>
<td>120 Periods</td>
<td>135 Periods</td>
</tr>
<tr>
<td>By GA</td>
<td>10.52</td>
<td>10.57</td>
<td>10.54</td>
<td>11.55</td>
<td>11.45</td>
</tr>
<tr>
<td>By Analytical Solution</td>
<td>0.97</td>
<td>4.22</td>
<td>62.48</td>
<td>598.12</td>
<td>2,453</td>
</tr>
</tbody>
</table>

Table 5.5: Comparison of computation times between the genetic algorithm and the analytical solution.

5.4.3 Effect on production costs

The economic effect of implementation of such strategies in the production process is an important factor in adoption. Table 5.6 shows the costs that have been determined by
both the GA technique and the analytical solution for the identical cases in table 5.5. Genetic algorithm solutions are of high quality, both in terms of time and for providing the minimum cost.

<table>
<thead>
<tr>
<th>Case</th>
<th>5 Jobs</th>
<th>10 Jobs</th>
<th>15 Jobs</th>
<th>30 Jobs</th>
<th>45 Jobs</th>
<th>60 Jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>32 Periods</td>
<td>48 Periods</td>
<td>80 Periods</td>
<td>95 Periods</td>
<td>120 Periods</td>
<td>135 Periods</td>
</tr>
<tr>
<td>By GA</td>
<td>222</td>
<td>393</td>
<td>593</td>
<td>786</td>
<td>1112</td>
<td>1393</td>
</tr>
<tr>
<td>By Analytical Solution</td>
<td>222</td>
<td>393</td>
<td>593</td>
<td>782</td>
<td>1099</td>
<td>1393</td>
</tr>
</tbody>
</table>

Table 5.6: Comparison of costs obtained by genetic algorithm and the analytical solution.

According to the percentage of saturation of production steps of the total number of steps available, the ratio of saving is illustrated in Table 5.7, which represents the reduction of energy consumption costs proposed by our scheduling algorithm compared with energy consumption costs when applying the "as soon as possible" scheduling strategy, which is commonly used by production schedulers.

<table>
<thead>
<tr>
<th>Case</th>
<th>Energy Cost By “As Soon As Possible” Scheduling Strategy</th>
<th>Energy Cost by GA</th>
<th>Ratio of Saving</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>267</td>
<td>206</td>
<td>0.23</td>
</tr>
<tr>
<td>2</td>
<td>273</td>
<td>198</td>
<td>0.27</td>
</tr>
<tr>
<td>3</td>
<td>326</td>
<td>222</td>
<td>0.32</td>
</tr>
<tr>
<td>4</td>
<td>418</td>
<td>393</td>
<td>0.06</td>
</tr>
<tr>
<td>5</td>
<td>382</td>
<td>366</td>
<td>0.04</td>
</tr>
<tr>
<td>6</td>
<td>7,062</td>
<td>6,435</td>
<td>0.09</td>
</tr>
<tr>
<td>7</td>
<td>7,676</td>
<td>6,691</td>
<td>0.13</td>
</tr>
<tr>
<td>8</td>
<td>7,870</td>
<td>6,109</td>
<td>0.22</td>
</tr>
<tr>
<td>9</td>
<td>7,372</td>
<td>5,796</td>
<td>0.21</td>
</tr>
<tr>
<td>10</td>
<td>654</td>
<td>593</td>
<td>0.09</td>
</tr>
<tr>
<td>11</td>
<td>876</td>
<td>786</td>
<td>0.10</td>
</tr>
<tr>
<td>12</td>
<td>1,363</td>
<td>1,112</td>
<td>0.18</td>
</tr>
<tr>
<td>13</td>
<td>1,600</td>
<td>1,393</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Table 5.7: Ratio of energy cost saving by the GA solution compared with the "as soon as possible" scheduling strategy.
From the analysis, it is possible to conclude that the most interesting application of this algorithm is in one of the following cases:

1. When the variances in energy prices during production shifts are high and demand is reduced as much as possible during the highest energy price periods.
2. When the energy consumption of the machine is high during its states and transition.
3. When the non-production times of a machine during a shift are high.

The proposed model could be used in discrete manufacturing. For example, it could be included as an extension of a manufacturing resource planning system (MRPII) to minimize the energy consumption costs of a machine by considering the changes in energy prices. The production planning would thus be accomplished in two stages: first at the facility level, for example, to define the number of jobs to be processed and the second phase at the machine level to define when each job will be processed. Here our model can be adopted.

The proposed model has some limitations, such as it focuses on machine scheduling, not on the scheduling of the actual sequence of jobs. In addition, the model does not accommodate different operational modes for a machine (e.g., high and low speeds), which will be investigated in further studies. The proposed model also does not change the job sequence to minimize makespan.

5.4.4 Environmental effects

In addition to the economic effect, adopting such strategies has a positive environmental effect. In fact, DSM objectives involve environmental issues such as reducing carbon emissions (Luo et al. 2010). Demand management strategies have a potential role in switching to sustainable energy systems by keeping energy demand at levels at which renewable energies can be sufficient to meet that demand (Pina et al. 2012). The increase in adoption of renewable energy plays a significant role in maintaining average global temperatures (Battaglini et al. 2009). Thus it is necessary to provide the decision-makers with information on the environmental issues related to their needs, for example, the
actual source of the energy, which may motivate decision-makers to consider the environmental effects of the decision-making process.
Chapter 6: Adopting IoT at the production system level – a methodology and facts

6.1 Introduction

This chapter aims to provide a methodology on how IoT technology (i.e., smart meters and sensors) can be adopted at the manufacturing shop floor level to increase energy consumption awareness and then improve energy efficiency of the production systems. The methodology includes evaluating of the maturity level of the current energy management system and production systems, recommendations for implementation at production level, analysis of the energy data, and integration of energy data in production management decisions. Then, evaluating energy consumption at a factory by implementing this technology (e.g., by using e-KPIs).

Note: the term “create a methodology” in this chapter means to create a toolbox including several methods aim to achieve the objective of adopting IoT technology at factories for the purpose of monitoring energy consumption. For example, this includes methods for evaluating energy management level, implementing of IoT technology, and integrating energy data in production management.

Given these introductory remarks, the chapter is structured as follows: Section 6.2 illustrates the methodology. The implementation of the methodology in a pilot study is explained in Section 6.3, which includes the evaluation of energy efficiency at the factories.

6.2 A methodology for adopting IoT to improve energy efficiency in production

Many techniques and tools are used to process improvements, such as DMAIC, which includes five phases: define, measure, analyze, improve, and control. In this chapter, these five phases of DMAIC are included in the proposed methodology. Based on the literature review, the methodology has been built as in Table 6.1; it consists of five
phases as follows. Then, the methodology was implemented at a factory during a pilot study as explained in Section 6.3.

<table>
<thead>
<tr>
<th>Phases</th>
<th>Main activities</th>
</tr>
</thead>
</table>
| **Phase One:** Evaluating and Understanding of the energy management and production processes | 1. Evaluating current energy management and production processes  
2. Understanding production processes at the factory  
3. Classifying of machines and defining strategies for each class  
4. Defining targets and expected benefits from adopting IoT – from a business perspective – this includes  
   - Defining the target of improvement (factory requirements)  
   - Defining e-KPIs that will be tested after collecting the energy data  
   - Defining expected benefits from clear energy awareness  
   - Defining the sustainable practices that will be applied in production management |
| **Phase Two:** Monitoring and analysis | 5. Defining metering requirements (i.e., measurement plan)  
6. Installing the monitoring systems and verifying the quality of the data  
7. Collecting and analyzing energy consumption data |
| **Phase Three:** Integrating energy data into manufacturing systems and tools | 8. Integrating energy data into available manufacturing systems (MES, MRPII, ERP)  
9. Using tools for supporting energy efficiency improvement  
   - Visualizing energy and e-KPIs  
   - Simulating Energy KPIs  
   - Developing energy-decision support system (e-DSS)  
   - Optimizing techniques |
| **Phase Four:** Integration energy data into production management practices and decisions | 10. Integrating energy data in production management  
   - Planning and scheduling production  
   - Configuring of production processes  
   - Managing maintenance  
   - Managing cost |
| **Phase Five:** Evaluating and control | 11. Evaluating energy efficiency improvement  
   - Evaluating the improvement opportunities  
   - Evaluation energy efficiency using e-KPIs  
12. Control and continuous improvements |

Table 6.1: A methodology to increase energy efficiency in manufacturing companies by adopting IoT as an enabler for energy consumption awareness
6.2.1 Phase 1: Evaluating and understanding of energy management and production processes

This phase aims to understand the business situation. It includes evaluating the maturity level of the energy management and production systems, understanding the production processes (i.e., production volume, available technology, and so on), and defining targets and benefits from increasing energy awareness (i.e., adopting IoT), as follows:

6.2.1.1 Evaluation of current energy management and production processes

As a starting point, this phase aims to evaluate the maturity level of current energy management practices and production processes. Such evaluation aims to define to what extent energy awareness and management can be improved. Several tools are available to evaluate energy management (Introna et al. 2014). Also the energy management matrix (EPA Victoria 2002; Gordić et al. 2010), which provides an approach to gain insight into the current status of an energy management effort within a manufacturing company. Furthermore, the energy management matrix seeks to identify the aspects that required more attention and investment for improving energy management practices to the desired level. Also, Ngai et al., (2013) provide an energy and utility management maturity model (EUMMM) for the assessment and analysis of the maturity level of energy and utility management in companies.

However, these evaluation tools and models do not provide enough details on the criteria and indicators for the evaluation. For that, Table 6.2 illustrates additional criteria (in the form of questions) to evaluate the current maturity level of energy management, and Table 6.3 evaluates production systems (focusing on standardization). Based on both evaluations, the maturity level is determined as in Figure 6.1. The circles in Figure 6.1 represent examples of potential positions of the current maturity level at a factory. Also, the maturity level that needs to be achieved can be represented using this figure. For example, if the position of the current maturity level has been identified at circle number one, this means by collecting real-time energy data from the machines, the new maturity level will not shift to the position at circle ten without increasing the maturity level of the
production processes and linking energy data with production data. But it could be shifted to position two or five by collecting the energy data and integrating them in production management.

However, the evaluation includes investigating the current capturing systems (e.g., energy meters and SCADA) to understand current measurement capability (see Table 6.2 and Table 6.3). In case there are meters that have already been installed, creating a metering diagram helps to understand current metering capabilities, including meters’ identification (ID) parameters.

### Assessment of current energy management

<table>
<thead>
<tr>
<th>Question</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Does the factory have energy management tools to improve energy efficiency?</td>
<td>If so, what are they?</td>
</tr>
<tr>
<td>Does the factory have an environmental ISO certificate (e.g., 50001)?</td>
<td>If yes, what is the certificate number?</td>
</tr>
<tr>
<td>Does the factory have current energy management practices and production levels recorded?</td>
<td>If so, what are they?</td>
</tr>
<tr>
<td>Do they use energy-KPIs to evaluate energy efficiency?</td>
<td>If so, what are the e-KPIs?</td>
</tr>
<tr>
<td>Does the factory have energy measures available (in terms of money or in terms of kW/h) to evaluate energy saving by adopting current energy management?</td>
<td>If there, how much is the saving?</td>
</tr>
<tr>
<td>What is the percentage of energy costs (i.e., energy bills) on operation costs and production costs?</td>
<td></td>
</tr>
<tr>
<td>Does the factory buy energy with variable prices?</td>
<td>If so, what is the price structure?</td>
</tr>
<tr>
<td>Are managers and workers involved in improving energy efficiency?</td>
<td>If so, who is involved? What are their rolls?</td>
</tr>
<tr>
<td>Do maintenance strategies connect to energy efficiency?</td>
<td>If so, how are they connected?</td>
</tr>
<tr>
<td>Does the factory track energy consumption data?</td>
<td>If so, how?</td>
</tr>
<tr>
<td>Does the factory have an energy monitoring system (energy meters) at the production level?</td>
<td>If so, does the factory track/check abnormal energy consumption during production process?</td>
</tr>
<tr>
<td></td>
<td>Also, does the factory integrate energy consumption data in the production management practices and decisions (e.g., scheduling)?</td>
</tr>
</tbody>
</table>
If so, where are these data integrating and to what extent?

- Does the factory have short and long term goals to reduce energy consumption and CO₂?
  - If so, how much? What is the plan to achieve that?

- Does the factory have barriers to improving energy efficiency?
  - If so, what are they?

**Table 6.2: Criteria to evaluate the maturity level of energy management at factories**

<table>
<thead>
<tr>
<th>Assessment of production processes at factories</th>
</tr>
</thead>
<tbody>
<tr>
<td>➢ Does the factory have production data available per machine on an hourly basis?</td>
</tr>
<tr>
<td>➢ Does the factory’s production schedule run automatically?</td>
</tr>
</tbody>
</table>
  - If so, using what? |
| ➢ Does the factory have manufacturing systems (e.g., MES, ERP)? |
  - If so, what are they? |
| ➢ Does factory have a production monitoring system (e.g., SCADA)? |
| ➢ Does the factory have maintenance reports per machine available? |
| ➢ Does the factory have detailed information on production processes available? |
  - If so, does the factory have production processes standardization? |
  - Does the factory have a database with all the processes available (individual operations)? |

For each production resource (e.g., machine, equipment, etc.),

- Does the factory have an updated list of available processes? |
- Does the factory have a valid configuration set of parameters, including the description of the performance and the expected quality levels?

For each production resource (e.g., machine, equipment, etc.),

- Does the factory have machine logs for the processes available? |
  - If so, does a log system record the events happening during the activity of the device? |
  - If so, does the factory have a logging system that is aware of the product ID being processed, which means that the logging record indicates the start and finish time for each process and product ID transformed at this production resource? |

- How many hours is each machine working per (day, week)!

**Table 6.3: Criteria to evaluate the maturity level of production processes at factories**
6.2.1.2 Understanding production processes at the factory

Understanding production includes describing the production processes and defining the production’s influencing factors. This step is essential to understanding the energy consumption patterns of the production processes, and then the opportunities for improving energy efficiency can be determined. At this point, drawing production process diagrams is necessary for better understanding the production processes. Such diagrams show the production processes sequence, processes setup, processing time, etc. When high levels of awareness are the target, the internal logistics between production processes have to be identified.

6.2.1.3 Classification of machines

The purpose of this step is to classify the machines according to machines’ power consumption (approximately at the early stage) and its operating time based on the historical data as in (Thiede et al. 2012). This classification helps in defining appropriate strategies for monitoring and improving energy efficiency. Also, this classification assists in identifying the specifications of energy meters (e.g., max power, etc.). The dissemination level of energy meters at a factory depends on several factors (e.g., level of energy awareness, budget, etc.). However, in case not all the machines will be monitored
by energy meters, this classification helps in defining priority of the machines that have to be measured.

6.2.1.4 Define targets and expected benefits from adopting IoT

In order to define the data that have to be collected, and to define the analysis level, the factory requirements (i.e., the main targets) for adopting IoT technology have to be identified in two directions. First, the required level of energy consumption awareness must be defined, which may involve defining the awareness required at the process, machine, production line, operation, and product levels. Second, the level of improvement and optimized energy efficiency must be defined, which may include factors such as reducing energy consumption, energy cost, CO₂, and so on. Also, defining targets also includes defining e-KPIs, which will be used in the evaluation after collecting the energy data. In fact, reducing energy consumption costs is one of the main motivations for adopting IoT (i.e., energy meters), but it is not the only benefit that can be obtained. So, using a benefit-driven method for adopting IoT technology (Shrouf & Miragliotta 2015) enables factories to select the benefits that fit their targets and maturity level. Such methods depend on linking the benefits with the energy management practices that lead to achieving the goal.

6.2.2 Phase 2: Monitoring and analysis

This phase aims to define the measurement plan, install IoT technology, then collect and analyze energy data.

6.2.2.1 Define metering requirements

Based on the required level of energy consumption awareness and improvement, the specifications for monitoring can be defined. At this point, creating a measurement plan that considers the following points is necessary:

- The machines that will be monitored and their energy data specifications (e.g., max power).
- Required measurements (i.e., units). For example, active power, reactive power, max/min of peak voltage, etc.).
- The interval time (i.e., capture time) per machine/process. Additionally, the accuracy level of the measurements.
- The suitable monitoring devices (i.e., smart meters) for each machine and its specifications. Here, the location and the environment of the meters (isolated, wet, accessible, etc.) need to be considered, as well as the maintenance needs of the meters.
- The communication system (i.e., wired, wireless, protocols) depend on the shop floor design.
- Where and how the data will be stored (e.g., locally or on cloud).
- The level of energy data needs to be analyzed (e.g., using EMS, regression models, data mining, etc.)

6.2.2.2 Install the monitoring systems and verify the quality of the data

Installing and configuring the system may include smart meters, sensors, gateways, and repeaters when needed. After that, the quality of the data collected should be verified (i.e., check the credibility). Several approaches can be taken for verifying the accuracy level of measurements, such as using a temporary meter for verification of the data collected, comparing current measurements against verified historical data, and using search-check-detect to find any irregularities in measurements.

6.2.2.3 Collecting and analyzing energy consumption data

Capturing, storing, retrieving, and analyzing data are the baselines to establishing an evaluation of the performance. The data is collected and subsequently analyzed and classified by energy management systems (EMSs). In general, EMSs store energy data in interval times equal to 15 minutes and one hour, and energy reports are sent to managers and supervisors. However, most EMSs available in the market provide reports that show energy consumption behaviors. So, more effort may be needed based on the factory’s
targets. The analysis of energy data can be performed at different levels. First is basic analysis and reporting, which includes showing energy consumption patterns, finding energy losses and poor performance, etc. Most EMSs available in the market perform this type of function. Second is statistical analysis for historical data. Third is using data mining and big data tools, which can be used to find relationships between energy data and other variables, such as speed, oil temperature, and so on. For example, the data can be exported to Google Fusion Tables directly (if the devices installed are compatible with the tables), which is a free product from Google that can be used to analyze time-series data.

6.2.3 Phase 3: Integrating energy data into manufacturing systems and tools

Energy-efficient decision making (e.g., at the operational level) can rely on collecting real-time energy data as well as on analyzing accumulated energy data (e.g., hours, days, weeks, etc.). So, in order to make energy-efficient decisions, energy data need to be integrated into available manufacturing systems (e.g., MES, MRPII). Furthermore, it is vital to use tools that support energy efficiency improvement, such as an energy-decision support system (e-DSS), optimization techniques, and simulation and visualization tools of energy consumption (cf. Chapter 4).

6.2.4 Phase 4: Integrating energy data into production management practices and decisions

Real-time energy data have to integrate into production management practices to enhance and enable energy-efficient practices. For example, integrating energy consumption data into production management affects planning and scheduling by choosing the efficient and effective machine configuration, selecting the most efficient machines, reducing the idle time between jobs, configuring the production processes, and so on (see Chapter 4). Additionally, maintenance management is enhanced by such data, and this is achieved by sending information related to machines’ problems almost in real-time to the maintenance department. Accordingly, the right maintenance action can then be
accomplished to avoid machine breakdown and reduce waste (Shrouf, Ordieres, et al. 2014). Furthermore, providing detailed energy data during production help to define the cost of energy consumed during production. So, this data can be used in defining the operational costs for a product.

6.2.5 Phase 5: Evaluating energy efficiency improvement

Evaluation of improving energy efficiency can be done by using several methods as follows:

6.2.5.1 Evaluating the improvement opportunities

Here, energy saving opportunities need to be evaluated. For example, energy data indicate the changing a tool or a filter of the machine reduce energy consumption. In such case, this opportunity need to be evaluated, define the payback period for the investment, define the factors that will be affected, and then present them to decision makers to evaluate the worthiness of the investment. Also, when there are several opportunities for improvement; these have to be prioritized.

6.2.5.2 Evaluating the use of energy-KPIs

Energy performance indicators (e-KPIs) help companies to achieve define goals and missions, because e-KPIs show the progress and shortage toward achieving improvement of energy consumption and evaluating energy use. Energy-KPIs enable managers to make better decisions and react to changes in energy use patterns. No single energy efficiency indicator can be applied in every situation, but the suitable indicators have to be defined depending on the decision tool to be applied or the decision to be made (Bunse et al. 2010). Based on the interviewees regarding the area of measurement of energy efficiency at manufacturing companies; Bunse et al., (2011) found that the factories lacked the means and appropriate e-KPIs to evaluate and compare energy usage in machines and processes. These lacking means include the following:
- Measuring to facilitate tracking changes and improvements in energy efficiency.
- Measuring to identify inefficient usage of energy within a factory.
- Using e-KPIs for mapping energy consumption to enhance understanding of the input, output, and measurement points for each manufacturing process.
- Measuring energy efficiency directly in monetary values to define a potential saving.

The availability of energy data increases the ability to use several e-KPIs to evaluate specific manufacturing processes, calculate the energy savings, and determine changes in short periods, which are difficult to calculate without detailed energy data. Data such as e-KPIs in (Bogdanski et al. 2012) were used at the department level and at the process level. Furthermore, factories can use methods to support developing e-KPIs (May et al. 2015).

### 6.2.5.3 Control and continuous improvements

The purpose of a control plan here is to continue to enhance the improvement gained. A control plan is needed, and all the improvements have to be documented.

### 6.3 Implementation of the Methodology – a pilot study

A Spanish factory was chosen for implementing the methodology; the factory specializes in machining and assembly parts. The main phases of the methodology have been implemented as the following steps.

One of the main factors for successful implementation of the methodology is the collaboration from the top management, middle management (e.g., operation manager and maintenance manager), as well workers at operational level (e.g., machines level maintenance). Without this collaboration, the implementation will likely fail to achieve the expected objectives.
6.3.1 Evaluating the situation’s energy management practices and production system

This first step aims to understand the current maturity level of energy management and production processes, mainly by evaluating the criteria in Table 6.2 and Table 6.3. This is done first based on meetings and discussions with the general manager, operations manager, maintenance manager and technicians. Next, in order to know the amount of energy used at the factory, historical energy consumption bills for the last 11 months were analyzed. Understanding how the total bills were derived is helpful, as is defining the energy consumption amount during peak time. In addition, the production quantities for same periods have been collected to gain an understanding of the relation between energy consumption and production level.

Actually, due to the lack of available data on energy consumption, at this phase, we ran an initial energy survey (i.e., walk-through audit) to identify the energy specifications of the machines. This walk-through included making an initial evaluation of the energy consumption and operating hours for each machine and tool. Based on that evaluation, the machines have been classified at the factory as in Figure 6.2 below, relying on the operating time and power consumption as in (Thiede et al. 2012). This walk-through was also used to understand the production processes sequences.

The evaluations indicated that the factory has limited energy management practices in place and that the maturity level toward the standardization of the production processes is low. For example, the quality data is available, but the machine log is not available regarding when each process was started and finished, and so on. Finally, the maturity level of the energy management and production processes at the factory is represented by circle number four in Figure 6.1 above.
Target and benefits of installing IoT (i.e., smart metering system)

Based on analysis of the current situation and discussions with top management followed by using the benefit-driven method, targets for and the benefits of improving energy awareness have been identified as the following (i.e., factory and researcher perspective):

- Understanding energy consumption awareness at the machine level.
- Using e-KPIs to evaluate energy efficiency at the process and machines levels.
- Defining the energy consumption during processing and idle status.
- Defining the available energy saving opportunities related to removing energy waste.
- Identifying unusual behavior in energy consumption for the machines in real-time by using a smartphone.
- Calculating energy consumption cost per produced unit.
- Analyzing energy consumption data and then re-evaluating the energy-efficient production management practices.

Figure 6.2: Energy portfolio as a tool for classifying machines
- Evaluating energy consumption before and after machines’ maintenance (e.g., change a filter and oil), so as to try to determine the best time for such maintenance to avoid higher energy consumption.

- Integrating energy consumption data into the production management (e.g., planning), to reduce energy consumption costs through the following:
  
  - Give the priority for the efficient machines for processing the jobs, then the next less efficient, and so on.
  - Reduce energy waste in idle machine time.
  - Define the energy consumption per machine under different configurations (speed) in order to select the most efficient configurations of the machines when possible, with consideration to quality and the deadline time of jobs.

### 6.3.3 Installation, collection, and evaluation of energy consumption data in the pilot study

After the target and benefits were defined, the measurements plan needed to be defined as illustrated in Section 6.2.2.1. Then, energy meters needed to be installed, and the gateway and energy management system (EMS) from the meters’ provider were configured. The energy data began to be collected from the machines and sent to the cloud in real-time. Most of the parameters were reported almost in real-time, such as energy (kWh), ampere, Volts, and Power factor. The collected data was checked for accuracy using the techniques mentioned earlier. The energy data was stored on the cloud (provided by the EMS provider). Furthermore, the EMS configuration employed a smartphone to receive instate messages concerning abnormal energy consumption behavior, and such messages were sent to the smartphone.

### 6.3.4 Evaluating energy consumption

Table 6.4 presents a sample of energy consumption data for one machine. These data were collected by smart meters and exported from EMS. Furthermore, these data accumulated for one hour, which means the level of awareness achieved was at the
machine level per hour. In fact, several e-KPIs can be used based on needs. However, when the aggregate level needed is at cycle time, operation time, and so on, data exports in one hour averages, as in Table 6.4, or even in 15 minute intervals are not useful, because energy consumption between the start and finish times of the processes can’t be specified. Also, specifying energy waste and idle time is difficult when data is exported in a one hour interval. Besides using the EMS and provider’s cloud, the real-time energy data have also been stored at the cloud so as to export energy data at any time. The ElasticSearch® database has been used due to its flexibility, such as storing structured and unstructured data, searches, etc. (Kononenko et al. 2014; Hashim 2014). In order to retrieve energy data form ElasticSearch® at any interval time, tools using R software have been built.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Machine</th>
<th>kWh</th>
<th>Amp1</th>
<th>Amp2</th>
<th>Amp3</th>
<th>Volt1</th>
<th>Volt2</th>
<th>Volt3</th>
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Table 6.4: Sample of energy consumption data that have been collected by smart meters from a machine

In order to evaluate the efficiency of using energy at the factory, a Lean Energy Indicator (LEI) has been used. It represents the ratio of energy consumed for producing products to
overall energy as shown in the following equation. In general, factories aim to achieve LE-KPI closer to 1 (May et al. 2015).

$$\text{LEI} = \frac{\text{Valuable energy consumption}}{\text{Overall energy consumption}}$$

$$= \frac{\text{Overall energy consumption} - \text{non-valuable energy consumption}}{\text{Overall energy consumption}}$$

Figure 6.3 represents the Lean Energy Indicator for one machine during three days; the machine was processing the same product during day 1 and day 2, and another product during day 3. The machine speed was set the same for the three days. The figure shows a variance in the indicator. Also, we find the average of LEI per day is 0.792, 0.795, and 0.5460, respectively.

![Figure 6.3: LE-KPI for a machine in production for three days](image)

Furthermore, based on analyzed energy consumption patterns for five machines over the course of 39 days, and linking it with production data, we found out that almost all of the machines stay at idle status during non-working periods, such as during coffee breaks, lunch times, and when there are no operations to be processed by the machine for several hours. The machines are turned off only on Saturday afternoon, Sunday, when they breakdown, and when no operations are available to be processed for long time (e.g., days). As a result of this behavior, the LEI for machine M007 is below 75% for 60% of
the hours the machine was not completely turned off. For example, the energy consumption pattern in Figure 6.4 shows that the machine was in idle status during one hour. And Figure 6.5 shows that the machine (same period in the next day) was processing, then it was switched to idle status for more than 60% of that hour.

![Figure 6.4: Energy consumption pattern during idle time](image1)

![Figure 6.5: Energy consumption pattern during one hour](image2)

In order to understand the energy consumption, more than 100 energy consumption pattern have been plotted and analyzed (e.g., per hour, 10 minutes, 2 minutes). Just to present some, Figure 6.6 shows the machine has an almost consistent pattern during processing. While Figure 6.7 shows the pattern for the same machine is not stable (i.e., there are peaks), during processes the same products (i.e., same type, and setup) in Figure 6.6. Also, while processing another product on the same machine, the energy
consumption pattern is not stable, as shown in Figure 6.8. Such peaks have effects on energy consumed, thus the factory needs to specify the causes of these peaks, and avoid them. One cause of such peaks is failing tools (e.g., machines’ arm) in putting the part that will be processed 100% in its place inside the machine. Other causes include faults with machining tools (e.g., cutting tools), which means the tools are not working properly. These causes have been identified by direct observation for the machines during production processes, and have then been linked to the machine behaviors with energy consumed in almost seconds. Because data were insufficient from the machine log, we did the observation manually. These figures present real-time energy consumption data of the machines, which are difficult to obtain by the expectation models, and such peaks can’t be defined or traced.

Figure 6.6: Energy consumption pattern of a machine during processing products for one hour
Generally, machines have different energy consumption behavior under different machine configurations (e.g., speed). For that, energy consumption during different machine configurations is evaluated. Figure 6.9 shows energy consumption of one machine processing same products (i.e., same type) under two different configurations. One machine’s configuration is set on speed (S1) 90% (Chuck one, Chuck two, and the Arm) for one hour. Then the speed configuration is set back to speed (S2) 100%. The machine consumes 5.7663 kWh under S1, and it consumes 6.0179 kWh under speed S2. Such data can be used to build energy-aware production schedules by selecting energy-
efficient machine configurations, while considering the other factors, such as quality, and the number of operations that are processed under each configuration at the same period of time.

Figure 6.9: Energy consumption pattern for a machine under different configuration

6.3.4.1 Evaluating energy consumption costs

Because energy costs represent one of the largest operating costs at this factory, and the operations cost is the main factor defining the products’ prices, a manager at the factory said that energy data used to define precisely what the energy cost is per piece and per order will be used accordingly to calculate the operation costs. From the point of view of the sales manager at the factory, this gives the factory a competitive advantage. Because reducing energy consumption costs has positive impacts on reducing the variable costs. Moreover, defining precisely the operations costs during production processes of an order gives the factory more flexibility in negotiating the product prices with the customer. In fact, previously they were estimating the energy consumption cost, which means operation costs were not precisely defined. Also, defining the energy costs enables them to provide the customers more than one offer (i.e., prices) based on the time the delivery order is due. For example, if the customer has flexibility with the deadline, an energy-aware production schedule can perform through shifting the production when possible to off-peak time (i.e., low energy prices) and select the most efficient machines and efficient-machine configurations, which leads to reduced energy consumption costs and thereby reduced operations costs.
6.4 Barriers that may be faced in the adoption of IoT and implementing methodology

These barriers were defined during the pilot study:

- Lack of motivation among top management.
- Low cooperation between mid-level management (e.g., production and maintenances managers); their cooperation is significant to integrate energy data in production management practices.
- Conflicts of interest between managers (e.g., energy and operation managers).
- Low level of current maturity in the energy management and production management standards.
- No trust between energy managers and workers at the operation level. The meters monitor the machines, but at the same time they provide insight into the behavior of the workers at machines – mainly if the production processes depend on the availability of the machines’ operators.
- Inability to estimate the Payback period of the cost of installation.
- Not well-planned for the implementation of the monitoring technology and the targets, expected benefits, and practices are not well defined.
- Lack of technical skills when high level of energy consumption awareness is required.
Chapter 7: Multi-level awareness of energy used in production processes

7.1 Introduction

Green products are not only those which consume less energy during use, but are also those products which have minimal environmental impacts as a result of production and logistics processes at the factory and across the supply chain. For that, environmental information related to production processes are becoming necessary at the factory level and for stockholders. This information can be provided in digital format (e.g., at the factory level, between suppliers and the factory, online), or showing on products packaging. In reality, consumers seek environmental information related to green products (Ritter et al. 2014). A “green appearance of the product” is one of the main consciousness factors influencing consumer decision making when choosing products (Maniatis 2015). Because of these, customers can judge the greenness of a product by simply looking at the displayed information on the product packaging.

In fact, real-time energy data enable factories to specify energy consumption and its costs during the production processes. Also, such data make it possible to think in terms of providing the stakeholder (e.g., consumer, governments) with accurate information regarding the CO₂ emissions that resulted from the production processes of products. For example, Table 7.1 presents nine energy-awareness questions (also called “energy-awareness queries”) that factories will be able to answer when having a high maturity level of energy awareness. These questions are grouped in three levels: first “energy-aware at operation level,” second “energy-aware at product level,” and third “energy-aware at order level.” The three groups include information specifying the energy consumed, the energy’s costs, and the CO₂ emitted through production.

In order to achieve that level of understanding, detailed production data are required, such as the start and finish times of each operation and the production sequence of each product. Also, this requires real-time energy consumption data, energy prices, and energy
sources (see Sections 7.2.2 and 7.3). Then, energy data have to be linked with the production data.

- **Energy-aware at operation level.**
  1. How much energy is consumed for processing per unit of the operation $X_i$?
  2. How much is the cost of the energy consumed in processing per unit of the operation $X_i$?
  3. How much CO$_2$ emissions are produced through processing per unit of the operation $X_i$?

- **Energy-aware at product level.**
  4. How much energy is consumed for producing product $P_i$?
  5. How much is the cost of the energy consumed for producing product $P_i$?
  6. How much CO$_2$ emissions are produced by producing product $P_i$?

- **Energy-aware at the per order level.**
  7. How much energy is consumed in producing order $O_i$?
  8. How much is the cost of the energy consumed for producing order $O_i$?
  9. How much CO$_2$ emissions are produced by producing order $O_i$?

**Notations**

i: i…n.          $X_i$: elementary operation of a process i.          $P_i$: product i.          $O_i$: order i

**Table 7.1: Energy-awareness questions**

Based on such integrations, this chapter provides a way to achieve multi-level awareness of energy consumed during production processes; it involves specifying the energy consumed, CO$_2$ emitted, and the cost of energy consumed at the operation, product, and order levels. That is, this awareness makes it possible to answer the nine questions and represents the energy consumed at the factory. Furthermore, the chapter proposes how to integrate such energy data from suppliers to specify the accumulated energy consumption data (at suppliers and the factory) for producing the final product.

Moreover: Calculating the energy consumed during production processes is one of the ways toward sustainable processes. In this regard, Faulkner and Badurdeen (2014) present a simple visual representation of estimated energy consumption data of production processes using sustainable value stream mapping (VSM), as shown in Figure 7.1. This VSM considers energy consumed in each process and in the logistics between
processes. So, the proposed energy awareness in this chapter enables lean manufacturing to present such VSM based on accurate data.

![Visual representation of energy consumption on Sustainable-VSM.](image)

**Figure 7.1: Visual representation of energy consumption on Sustainable-VSM. (Faulkner & Badurdeen 2014)**

Given these introductory remarks, the Chapter is structured as follows: Section 7.2 illustrates the concept of multi-level energy awareness and Section 7.3 explains the requirements for achieving such energy awareness. Then, Section 7.4 introduces a way to enhance multi-level energy awareness at the operation, product, and order levels. Regarding future developments, Section 7.5 proposes how to increase energy awareness at the product and order levels by integrating energy data from across suppliers.

### 7.2 What is multi-level energy awareness

Collecting real-time energy consumption data by installing smart meters at the machine level makes it possible to increase awareness of the energy consumption at several levels, including the operation, product, order, machine, production line, and production levels. Based on factories’ orientation, energy awareness can be classified in two ways as shown in Table 7.2. First, energy-awareness orientation for machinery aims to increase awareness at the process, machine, production line, and production system levels. Second, energy-awareness orientation for products aims to increase awareness per operation, per product, and per order.
<table>
<thead>
<tr>
<th>Monitoring level</th>
<th>Awareness type</th>
<th>Awareness orientation</th>
<th>Awareness level</th>
<th>Main beneficiaries (level of benefits)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine level</td>
<td>Energy consumed</td>
<td>Machinery</td>
<td>Process level</td>
<td>Factory level</td>
</tr>
<tr>
<td></td>
<td>Cost of energy consumed</td>
<td></td>
<td>P machine level</td>
<td>Factory level</td>
</tr>
<tr>
<td></td>
<td>CO₂ emissions</td>
<td></td>
<td>Production line level</td>
<td>Factory level</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Production level</td>
<td>Factory level, Stakeholders</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Operation level</td>
<td>Factory level, Stakeholders</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Product level</td>
<td>Factory level, Stakeholders</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Order level</td>
<td>Factory level, Stakeholders</td>
</tr>
</tbody>
</table>

Table 7.2: Energy awareness level based on awareness orientation

7.2.1 Energy awareness level

Energy awareness at machine level means a machine’s energy data are collected, retrieved, and analyzed to define its energy consumption pattern. Also, energy awareness at production line aims to define the energy consumption for a sequence of machines that process one job. Also, the total energy consumption of several production lines provides energy awareness at production system level. Furthermore, energy awareness at process level aims to understand the energy pattern for processing an operation at one machine or more (e.g., cutting 100 pieces); here, the aim is to define the energy consumed without linking the process to a specified product. These four levels represent the first orientation (i.e., machinery), cf. Chapter 6.

Specifying energy awareness at operation level means to specify energy consumed for one operation (e.g., cutting one piece) for a specified part or product; this is done by calculating the energy consumed between the start and finish times for the operation. Specifying energy consumed at the operation level makes it possible to calculate the energy consumed for producing one product (i.e., energy awareness at product level). This awareness can be achieved by assessing the total energy consumed during all operations that are done for processing the product. In addition to that, the energy consumed in logistics can be added to the total energy consumed. Here, logistics is
considered one operation of the part/product, so it has time and energy data. Thanks to Internet of Things technology, the start and end time for moving a component can be defined automatically, and accordingly, energy consumed for the logistic operation can be calculated. When a bundle of components has been moved, the energy consumed for moving them divided by the number of components that have been moved will calculate the energy consumed per component. However, the way of calculating the energy in logistics can vary between factories. For example, (Hopf & Müller 2015) use an energy card to determine the energy demand of a logistics area in a digital factory. Finally, **energy awareness at order level** can be defined by the total energy consumed for producing all products in an order. These three levels represent the second orientation (i.e., product), which is the focus in this chapter.

### 7.2.2 Type of energy awareness

This section illustrates types of energy awareness that can be achieved by collecting real-time energy data.

#### 7.2.2.1 Specifying energy consumed and its cost

In fact, energy consumption cost is a vital issue for factories, mainly because energy costs in manufacturing plants commonly represents the second largest operating cost in several industries (Davis et al. 2012). However, specifying energy consumed at the operation level useful for factories, because it can be used to improve energy efficiency. Also, it enables factories to specify the energy consumed for a product or an order. In addition to that, it makes it possible to calculate the cost of the energy consumed for processing each product and then each order. Because energy prices are variable during a day (e.g., hourly basis), the cost of energy consumed for processing a product can be calculated by aggregating the costs of energy consumed for all operation made for producing the product.
7.2.2.2 Specifying CO2 emission from energy consumed

In addition to determining the energy consumed and the related costs, energy awareness at the operation level enables factories to calculate the amount of CO$_2$ emitted for processing one product as well as a total order, and can then provide such data to their stakeholders. Simply stated, this can be achieved by first calculating energy consumed for processing the product and then calculating the amount of CO$_2$ emitted from generate energy that has been used in producing the product. In a general way, energy providers give CO$_2$ data to their customers, as noted by (Iberdrola 2015). At the present, some energy providers sell 100% renewable, as noted by (Gesternova 2015). In reality, manufacturing companies can buy energy from several energy providers, which motivates them to make energy purchasing decisions with considerations of the energy sources and energy prices – buying energy either generated from renewable sources or from non-renewable sources. Furthermore, some factories generate part of their energy from renewable sources on-site and buy the rest. For example, a factory could buy energy from 8:00:00 to 8:59:59. Then, it generates energy from a renewable source from 9:00:00 to 10:00:00, and so on. In such cases the factories can calculate CO$_2$ emissions (e.g., per product) not only based on the amount of energy consumed in processing the products, but also based on energy sources used to create that energy. For example, if the amount of energy consumed for producing two products is equal, this does not mean the CO$_2$ emitted for producing the same products is equal, because energy sources are different (nonrenewable & renewable) see Figure 7.2. So, in this chapter, sources of energy are taken into account in calculating CO$_2$ emitted. However, this enables the factories to show their stockholders how much of the production processes of a product were green.
Figure 7.2: An example of different energy sources and their CO₂ emissions

7.3 Requirements for enhancing multi-level of energy awareness

In order to carry out the above multi-level energy awareness, machine, process, and energy consumption data have to be available, standardized, and integrated.

7.3.1 Energy consumption data

The required level of energy awareness is a significant factor in defining energy consumption data that need to available. However, for specifying energy consumption at the operation level, energy consumption data have to be collected in real-time from machines and equipment and the interval time has to be in seconds. Also, time to export energy data is preferred to be as short as possible (e.g., 1 and 2 seconds). In such cases, energy consumption data can be exactly specified between the start and finish time of each operation. For clarification,
Figure 7.3 shows an energy consumption pattern for a machine during production operation. It also illustrates a sample of start and finish times for seven operations. Based on the start and finish time, energy consumed for each operation can be calculated. The energy peak in the figure calculates part of the energy consumed for producing the operation at that time.

![Figure 7.3: Energy consumption for production processes on a machine](image)

7.3.2 Production data

In order to specify the energy consumed for each process and product, energy data have to be linked with production data as well as to the product’s quality data. For that, a high maturity level of process standardization is expected to be reached. Thus, such factories should be expected to have the following components:
The technical specifications for all the processes available at the factory properly coded and stored in a digital form, being ready for machine to machine (M2M) queries.

The mapping between each production resource (machine, equipment, etc.) and the processes available.

The valid parameter configuration set, including the description of the performance and the expected quality levels. Those sets will be in relationship with the production resources and processes.

The manufacturing system (e.g., Manufacturing Execution Systems (MES), Advanced Production and Scheduling systems, Manufacturing Resource Planning (MRPII), or Enterprise Resource Planning (ERP)). By means of those systems, production plans per order and/or product will be digitally established and it will be served upon request both for human consumers but also for M2M dialogs.

A log system recording all the events happening during the activity of the device; the logging system need to be aware of the product ID being processed at any resource, which means that the logging records indicate the start and finish time for each process and product ID transformed at this production resource in the specific process or operation.

In case a factory wants to include energy data from suppliers, there also needs to be an automatic exchange of consolidated records related to energy data per item. This requirement and the need for details in specific cases will push for a similar level of standardization with the tier-1 suppliers, when specific agreements for sharing those low-level records are enforced. The exchanges of data can happen by using EDI protocols or direct M2M exchanges. In this way, the paradigm that a factory produces and exchanges products and data becomes absolutely true (Zuehlke 2010; Shrouf, Ordieres, et al. 2014).

Figure 7.4 shows a class diagram (i.e., data entities) that describe the main structure of energy-aware production management. It includes ten classes, which are classified into three sets. The first set (colored gray) includes order, part, and product classes, which represent information on orders and products. The second set (colored white) includes job, shift, process, and machine classes, which represent information on scheduling and
operations logs. And the third set (colored green) includes energy meters, energy provider, and Energy sources, which represent information on energy information that is consumed for processing. For more details, the classes are discussed below.

![Class Diagram](image)

Figure 7.4: Class diagram for energy-aware production management

The order class represents an order by a customer. Its attributes include at least the order ID, quantity, product specifications, quality requirements, and due time. The connection (i.e., association) with products enables it to track and calculate CO₂ emitted for producing all the products in the order, including the emissions from bringing the orders to customers.
The **product class** represents products that have been produced at the factory. Its attributes are a unique ID, time input, and time output (represent start and end times of production). Finally, the connection with the **part class** and **process class** enable factories to define the energy consumed, energy costs, and the carbon emitted for producing each product at the factory. This includes the energy for processing its parts, assembly (if required), packaging, and logistics processes. The calculation of energy consumed in processing is based on the data from energy meters and the machine log. Energy data for each product are calculated individually.

**Part class** is a component included as part of a product (i.e., raw material). Energy consumption data is calculated for each part individually.

For **job class**, a job is defined as a net requirement of a part to be processed during a period of time. Generally, an order transforms into a set of jobs during planning processes. Its attributes include job ID, start time, and end time, which are defined during the scheduling processes.

**Shift class** is used in scheduling processes, and its attributes include Shift number, start time, finish time, and resources (e.g., employee).

**Operation class** represents the processing of a specific part and product at a machine. The attributes of this class include Operation ID, processing time of the operation, and start time, which are used for calculating the total processing time defined by when the process has been started and when it finished. The operation setup attribute is used to identify the description of the operation (i.e., one process). The connection between this class and the **machine class** is that the latter is used to identify on which machine the process had taken place (manufactured). Also, the connections between the **part class** and **product class** identify which part has been processed and belongs to which product.

The **machine class** represents any machine in the factory; its attributes are machine ID, configuration, and operation code. The connection between **machine class** and the **energy meter** class is one-to-one, it indicates each machine is monitored by one energy meter.
The *energy meter* class represents a metering device installed to monitor energy consumption per machine in real-time. Its attributes including meter ID, date, time, and energy consumption, which it uses to identify energy consumption data for each machine at any time. The *energy provider* class represents providers of the energy; it may include the factory itself when the factory generates energy on-site. However, its attributes date, time, and energy prices are used to define the energy prices at different times (e.g., hourly bases). Also, the link date, time, and CO₂ emissions per kWh are used to define the CO₂ emitted for energy consumed at that time. *Energy source class* is used to define the sources that have been used to generate the energy (e.g., renewable, coal, gas).

### 7.4 How to enhance multi-level energy awareness

In order to be smart enough, the previous data need to be available both to the people working at the company, depending on their access level, and in a synchronous way with the machines at the factory. Thus, this chapter proposes to use Business Process Modeling Notation (BPMN) and XML Process Definition Language (XPDL) descriptions as an adequate standard representation for processes, even though any other choice keeping in mind the human and machine information levels is also valid.

The BPMN specification provides a graphical notation for expressing business processes in a Business Process Diagram (BPD), able to represent complex process semantics. Also, it provides mapping between the graphics of the notation to the underlying constructs of execution languages, such as the Business Process Execution Language for Web Services (BPEL4WS) (Lapadula et al. 2012) and the Business Process Management Language (BPML). As the Workflow Management Coalition (WfMC) works with BPML, mapping from BPMN to XPDL has been created, thus XPDL is proposed to be used in this application.

By using tools that enable such languages without the loss of generalization capabilities, a new order for producing several products/parts can be considered, like carrying out one job among several. In such a case, the order will need to be completed based on the
logical architecture designed for the order at the factory and in regard to the availability of resources. Such would be true of a job that involves a single part to be repeated until the total number of parts requested by the customer are completed. Technically, the identification of processes, their sequence, the quality, and time constraints need to be specified on a per job basis. This step used to be carried out at production engineering department and it can include several alternatives.

After doing this, the scheduling itself can be accomplished. The scheduling needs to consider pre-existing workloads at different production devices as well as different criteria, like costs and delivery time, but also several others like energy consumption or CO₂ emissions, including internal transportation, raw material availability in time, etc. As depicted in (Shrouf, Ordieres-Meré, et al. 2014) a full automatic algorithm can be used to optimize the multicriteria fitted strategy the company has established. The relevant thing here is that based on the above machine readable description, artificial intelligence techniques can be used to produce the automatic allocation of resources with a clear idea about all the parameters the company or its customer is interested in, out of the goods themselves. The approach can be scaled up to the total order.

If it is done in this way, the outcome of the scheduling step will be an XML file with the specific resources used to produce the good with a specific ID as well as the assigned settings and the allocated time windows. Its extension to the full order is just the repetition for all the products and parts involved in it.

The advantage of such a model and data-integrated environment is that now, by using the logging system in combination with the designed production strategy per product as planned and according to the energy used, it becomes possible to track the original schedule and to identify variations, if any, as well as to provide a rich data environment to identify their different sources. The Figure 7.4 shows the class diagram for such integration of information.

Furthermore, energy data from smart meters need to be collected by using an XML or JSON (JavaScript Object Notation) base format. Thus, by automatically considering from
the logging system the time window for producing every product ID, it will be possible to
determine the amount of energy spent per product and process, and if the energy origin is
known, then the CO\textsubscript{2} emissions can be fully calculated automatically as well.

In this regard, the environment described here is fully embedded into the so-called
machine data as any resource is producing streams of machine data every second of every
day of operation for the resource. Thus, machine data contains a record of all the relevant
activity and behavior of the workers, transactions, machines, networks, applications, etc.,
including configurations, message queues, and events themselves. Machine data comes in
an array of unpredictable formats, and the traditional set of monitoring and analysis tools
were not designed for the variety, velocity, volume, or variability of this data.

It is worth clarifying that, under this concept, no prior feature selection and definition is
to be stored into a specific column of a table as it was done in former times but the events
themselves are stored as they are, including their own individual structure. To allow this,
the big data solutions help in providing no SQL schema-less databases like CouchDB\textsuperscript{®}
from the Apache foundation, among others. The drawback with schema-less solutions
relates to indexing, but again, smart solutions from big data environments like
ElasticSearch\textsuperscript{®} allow live indexing with hotwired connections to the main database by
means of rivers.

By doing this in this way, information are not lost as every single event is recorded and
quickly accessible by any index still present, then causality analyses can be performed in
an unbelievable way looking for root causes of variations.

Still, huge amounts of semi-structured data need to be managed, such as those coming
from energy meters. But again, big data tools are there to help, like HBase, Cassandra,
Hyperbase, or those commercial solutions like SAP HANA, BigTable, etc.

As the solutions in the big data world (including Cloud computing) deal with enormous
data collections, to have continuous data production from several hundred or thousand of
IoT devices (smart meters, resource controllers, etc.) producing data at the factory level
does not mean any problem. Indeed, to integrate similar information from different facilities for the same company becomes natural under this paradigm.

Even more, as this can be carried out in an automatic way, different levels of awareness can be considered per process, per machine, per item, etc. In order to consolidate these data, they can be integrated in the production and management information system associated with the product ID. From this created knowledge now at the operational decision support system (OPDSS), the company’s decision maker will be able to make decisions with a higher level of awareness (Shrouf & Miragliotta 2015).

The sense we use in this chapter for the automatic way of doing things, like determining the energy invested in processing one specific item, its specific CO₂ emissions, etc., requires some data processing, starting from the data storage we have introduced in previous paragraphs. As far it needs to deal with new data streams, the lambda architecture, which was proposed by (Marz & Warren 2012) is recommended. This architecture is based on several assumptions:

- Fault tolerance
- Support of ad-hoc queries
- Scalability
- Extensibility

That architecture is composed of the following components:

- Batch Layer - responsible for managing the master dataset and for precomputation of batch views
- Serving layer - indexes the batch views for fast ad-hoc queries
- Speed Layer - serves only the new data, which has not yet been processed by the batch Layer

The batch layer can be implemented with the use of systems such as the already mentioned CouchDB or just Hadoop. The batch layer is responsible for storing the
imputable master data streams. Furthermore, with the use of the Map-Reduce algorithms, it contiguously computes views of this data available to the various applications.

The serving layer is responsible for serving the views computed by the batch layer. This process can be facilitated by additional indexing of the data in order to speed up the reads, which can be achieved by means of the already described ElasticSearch® tool.

Finally, the role of the speed layer is to compute in real-time the data that has just arrived and has not yet been processed by the batch layer. It serves this data in the form of real-time views, which are incremented as the new data arrives and can be used together with batch views for the complete view of the data.

The lambda architecture for processing big data can be modeled as a heterogeneous multi-agent environment (Alrokayan et al. 2014; Assunção et al. 2014). The communication can be simplified using the multi-agent system approach (Babiceanu & Seker 2015). Each agent is responsible for a specific task in data processing. For example, an agent would process end event messages per resource type and then look for the related start event, and after the time window is estimated, the effective energy can be calculated, aggregating the results and preparing fixed features in specific views for further analyses, etc.

Agents are autonomous and distributed. Cooperation between agents is done using message passing, where all the agents are communicating in the same manner. Therefore, the integration is simplified.

The described meaning for the concept of automatization over the data machine is not the only one available as implementations based on SQL on streams or many others can be identified in the available literature. The goal was to describe a plausible architecture making possible such a high degree of automatization.

7.4.1 A scenario to Requirements to enhance multi-level energy awareness
This sub-section presents one case to illustrate how these technological gadgets can be useful for obtaining information on energy consumed during production processes (e.g., to answer the questions in Table 7.1.

The case represents an order including three products. Alongside with delivery of the order, it is requested to provide the customer with an environmental report that indicates the energy consumed and the CO₂ emitted for producing each product and then the order as a whole. In addition, inside the factory, it is requested that the cost of energy consumed during the production of the order be defined.

Figure 7.5 shows a workflow for production process of the three products. The process starts from receiving the order, then identifying the requirements and scheduling the order. The product needs to be processed at two machines, and then the order will be delivered to the customer with the environmental report. The attributes of the process activities task application have been presented in the class diagram in Figure 7.4. Scheduling the customer’s order includes defining the machine, shift, and job classes.

In order to collect energy data at the operation level, energy meters have been installed at the machines included in the production process. The energy consumption data have been collected in real-time; the interval time was 1 second. Because energy management systems that export energy data in 15 minute intervals are not useful, the energy data are stored on the cloud and ElasticSearch® has been used to store and process the data, and then code using R software has been built to retrieve the energy data (cf., Chapter 6). This provides flexibility to retrieve energy data for any time, and calculates energy consumed between the start and finish time of each operation.
Figure 7.5: a workflow diagram for a production process

Notes for the case: the factory buys energy from two providers (e.g., hourly bases); one of them generates 63% of the energy from renewable sources. So, CO\textsubscript{2} emissions from Provider\_A is 0.513 Kg/kWh, and from Provider\_B it is 0.19 kg/kWh. Also, the energy prices are variable. In this case, energy price from 8:00:00 to 8:59:59 is 0.112 euro. From 9:00:00 to 9:59:59 is 0.135 euro, and so on.

Table 7.3 presents a summary of machines logs, and energy data the three products. Energy consumption in the table is calculated based on the start and finish time for each process, as in Figure 7.3.

<table>
<thead>
<tr>
<th>Part ID</th>
<th>Product ID</th>
<th>Process ID</th>
<th>Machine Numbr</th>
<th>Processing time</th>
<th>Start time of processing</th>
<th>Finish time of processing</th>
<th>Energy consumption kWh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xxx</td>
<td>GBM1</td>
<td>M222</td>
<td>M007</td>
<td>5 m</td>
<td>8:35:00</td>
<td>8:39:59</td>
<td>0.51</td>
</tr>
<tr>
<td>Xxx</td>
<td>GBM2</td>
<td>M222</td>
<td>M007</td>
<td>5 m</td>
<td>8:40:00</td>
<td>8:43:59</td>
<td>0.51</td>
</tr>
<tr>
<td>Xxx</td>
<td>GBM3</td>
<td>M222</td>
<td>M004</td>
<td>5 m</td>
<td>8:40:00</td>
<td>8:43:59</td>
<td>0.505</td>
</tr>
<tr>
<td>Xxx</td>
<td>GBM1</td>
<td>C332</td>
<td>M002</td>
<td>4 m</td>
<td>9:10:00</td>
<td>9:13:59</td>
<td>0.419</td>
</tr>
<tr>
<td>Xxx</td>
<td>GBM2</td>
<td>C332</td>
<td>M002</td>
<td>4 m</td>
<td>9:14:00</td>
<td>9:17:59</td>
<td>0.418</td>
</tr>
<tr>
<td>Xxx</td>
<td>GBM3</td>
<td>C332</td>
<td>M002</td>
<td>4 m</td>
<td>9:18:00</td>
<td>9:21:59</td>
<td>0.416</td>
</tr>
</tbody>
</table>

Table 7.3: Summary of production scheduling and machines logs
XPDL is used to process logging data and energy detailed data needed to calculate the energy consumed, CO₂ emissions, and the cost. Then, an agent is needed to calculate energy data per operation ID. The agent first needs to calculate energy data for each operation done on the product, then sum the values.

A second agent is needed to track the sequence of scheduling and select information per product ID; this will clarify the energy per product. This will be stored at the upper level in the class model.

The third agent is needed to look into the summary records database, the process log, and the process definition database in such a way that processes’ parameters based on data can be analyzed against the process log and summary records. Therefore, events can be analyzed and rules to improve the knowledge management can be derived. This is possible due to the event based log recording, instead of recording the predefined set of features. The benefit of such an approach is that derived rules will increase the accuracy due to the new collected data.

### 7.5 Multi-level of energy awareness across suppliers

Green and sustainable supply chain management has several definitions, and each definition addresses one or more characteristics, such as “flow focus,” which includes flows of materials, services, or information (Ahi & Searcy 2013). Liu et al., (2014) indicate smooth information flows among supply chain members can facilitate Green Supply Chain Management implementation.

Based on the capability of having multi-level energy awareness at the factory level, the question arises: How can factories specify energy consumed and CO₂ emitted for producing final products, including processes at the factory and its suppliers (e.g., first-tier supplier, second-tier)? This can be done by specifying energy data during adding value processes of a product across a supply chain: for example, from second-tier suppliers to the final factory (i.e., OEM).
Generally, OEM determines specifications of the components that they are buying or processing from suppliers to be part in the final product. So, OEMs can also request their suppliers provide energy consumption data with these components. Figure 7.6 presents an energy consumption information flow of a product from suppliers to OEM. It shows that second-tier suppliers calculate energy data (e.g., energy consumed and CO₂), and provide them to first-tier suppliers with the components. Additionally, a first-tier supplier may calculate the energy consumed at its factory, adding to the energy received from second-tier, and then providing the total energy data to the OEM. In reality, the OEM can determine whether to receive energy data only from the first-tier or total energy consumed data at both tiers. However, at this point, the OEM calculates energy data for the final product by adding energy consumed at the OEM to data received from first-tier suppliers.

For example, in order to calculate CO₂ resulting from producing one product, each second-tier supplier calculates CO₂ emissions that resulted from producing its components (e.g., in Figure 7.6, components A1, A2, A3, etc.). These data are provided automatically to the first-tier supplier (e.g., using EDI). Also, the first-tier supplier calculates CO₂ emissions resulting from production processes at its factory (e.g., component A) and add these data to the CO₂ data collected from the second-tier supplier. Similarly, the OEM receives energy data from first-tier supplier and adds to the CO₂ data the resulting emissions data from its production process. At this point, CO₂ emitted can be provided to the OEM’s stakeholders. In order to achieve that end, collaboration and standardization between the OEM and the suppliers is needed.
The energy data from suppliers can be managed by the product manager. Figure 7.7 depicts a class diagram for energy data from OEM and suppliers flow for producing a product. It includes four classes supplier class, part class, energy data at factory class, product class. The supplier class represents the first-tier suppliers of the factory, its attributes are Supplier ID and Supplier Name. Part class represents all components that are received from first-tier suppliers. Its attributes include Part ID, CO₂ emitted at suppliers, and energy consumed at suppliers. These attributes are used to specify energy data consumed for producing each part at the suppliers side. Energy data at factory class is data related to energy consumed for producing a product at a factory. Finally, product class is a product at the factory. Its attributes include product ID, Total energy, and Total CO₂ emissions, which are used to specify total energy data for the production of the product, including data for energy consumed at the factory and received from the first-tier supplier.
From the technological point of view, these data sets should be located on the cloud in such a way that, with proper authorization, all the suppliers may upload their summary records regarding each product, still keeping a high level of traceability when required. This could even allow final or intermediate customers to browse the records to calculate their own carbon footprint.

Because of the suggested class diagrams, big data column oriented databases like HBase, Cassandra, Hyperbase, or those commercial solutions like SAP HANA, BigTable, etc., will help the most to operate such data pools in a useful way.

In the coming IoT-fueled big data era, it will be possible to enlarge these kinds of repositories by storing energy consumed by the operation of those products as well.
Chapter 8: Conclusions, managerial recommendations and

This thesis provides novel methods to utilize IoT paradigm at discrete manufacturing for improving the energy awareness and efficiency of production processes at the machinery and product levels. The thesis offers the following conclusions.

First: the study in chapter four 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 through 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.

Relying on a literature review and on an empirical data (expert interviews, online available sources), the topics (in chapter four) are addressed, which these are relevant for managers. Differently from traditional “solution-driven” views, it presents a backward approach to guide to this process: starting from the most important question (“What benefits do I want to achieve?”), the thesis 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 study in chapter four 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. 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.

**Second:** when reducing energy consumption costs, environmental factors become important in manufacturing practices. The study in chapter five provides a mathematical model to minimize the total energy consumption costs for single-machine scheduling, considering the continuous changes in energy prices. The model helps an operations manager or a decision-maker choose the most efficient production schedule to minimize the costs of energy consumption.

The results indicate that significant savings may be achieved when considering continuous changes in energy prices in a production schedule. Although the primary purpose of this study is to reduce production costs, our results reduce energy consumption during peak times across the board, thereby reducing the negative environmental effects of high energy demands during certain periods of the day.

The energy consumption costs of a machine generally depend on several factors such as the duration of each machine status and transition, energy consumption during each phase, and energy costs; however, adapting variable energy prices to production time (i.e., time of energy usage) has become a significant variable in generating total energy consumption costs.

In addition, an analytical solution has been developed to obtain the optimal solution, depicting a comparison between analytical and heuristic solutions. This solution shows that the heuristic solution provides the optimal solutions in most test cases and nearly optimal solutions in others. In particular, optimal results are obtained when the size of the gene population increases. The analytical solution provides the optimal solution in acceptance time for short problems (i.e., limited schedules). When the computation time for longer schedules is relatively high, the heuristic solution is preferable. In addition,
using the Sferesv2 C++ framework to implant such a problem helps the code run more quickly. This algorithm exhibits the potential capability of being deployed at factory level.

Third, Chapter 6 illustrates the high level of energy-awareness that can be achieved by collecting and analyzing real-time energy consumption data at the machine level (enabled by IoT technology). It provides evidence that adopting IoT for monitoring energy (at the machine level) enables factories to identify when, where, and how much energy is being wasted and to identify the real level of energy efficiency in the production process. That is, real-time energy consumption data enable factories to find new opportunities to improve energy efficiency, and this confirms some practices that have been identified in Chapter 4. Additionally, Chapter 6 has shown that the level of energy savings that can be achieved depends on several factors, such as flexibility in production schedule, level of integrating energy data with production data, collaboration of the operation manager and workers at the shop floor. Also this thesis confirms that energy-awareness enhances some competitive advantages by improving energy efficiency (which leads to reduced operations costs), and by defining energy consumption costs at the product level.

Fourth: Thanks to IoT technology (e.g., smart meters, big data tools, M2M), the energy consumption data can be collected and tracked at the operation and product levels as discussed in Chapter 7. This study illustrates to what extent the integration of real-time energy consumption data at the machine with production level data increases energy-awareness. In fact, this makes it possible to specify the energy consumed, energy cost, and CO₂ emitted for production down to the single operation, single product, and single order. It also enables factories to specify the CO₂ emitted for producing a product based on the energy sources that have been used in production. Finally, in order to develop better practices and strategies for green and sustainable manufacturing, this study enables lean manufacturing to add specified and accurate energy-related data (metrics) to their Value Stream Maps to identify their environmental impact, identify waste, and identify high energy processes for further analysis and improvement.
8.1 Further work

The energy practices collected in Chapter 4 could undergo a conventional hypothesis testing (e.g., through a survey methodology) to enhance the generalizability of that part of the thesis’s contribution.

Further work on the mathematical model and algorithm provided in Chapter 5 is to include non-dominated multicriteria optimization by considering both continuous changes in energy prices and how to “minimize makespan.” Another extension of the study could connect optimization at this level with the job scheduler strategy in both directions, allowing the inclusion of additional penalty factors such as machine maintenance and extending the shift duration. Since the considered problem in Chapter 5 is minimizing energy cost for a single machine, other contributions can consider the changed energy prices with other variables (e.g., minimizing makespan, penalty factors, etc.) in flow shop scheduling.

Also, the proposed mode of energy information flow from suppliers (e.g., first-tier and second-tier suppliers) to the OEM in Figure 7.6, which aims to precisely define energy consumed and CO₂ for producing a product, needs to be tested. Action research methodology appears to be the most feasible approach to such testing. Later, when factories start labeling their products with the level of CO₂ omitted for producing the product, in addition to the energy label that shows the level of energy consumed during the use of the product, studies could investigate what the impact of adding such a label would be on the purchasing decisions of the consumers. This data could be compared with the impact of the current energy label. Moreover, another contribution could study the impact of forcing factories to increase energy efficiency and use renewable energy sources in production processes to show how much their product is green.
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