Università Politecnica delle Marche
Scuola di Dottorato di ricerca in Scienze dell'Ingegneria
Corso di Dottorato in Ingegneria Industriale

A Method and Tool to improve the energy efficiency of production systems in the context of Smart Manufacturing

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XXXIII edition

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Abstract

Climate change is the main challenge for the 21^{st} century society. The latest IPCC report (2018) highlights that the increase in global greenhouse gas emissions is rapidly altering the climate and states that, if nothing is done, the climate change will deeply influence future development opportunities. The industrial sector, which represents about one third of global final energy use and 40% of global energy-related CO_2 emissions, could make a significant contribution in this regard.

Research and innovation for the factories of the future is not only a matter of developing and integrating new technologies, but also a challenge to make manufacturing less dependent on energy. Energy efficiency represents an important action for mitigating the environmental impacts of manufacturing processes, and it is the first step towards the implementation of sustainable production.

The goal of this thesis is to develop a method to support companies in the enhancement of energy efficiency in manufacturing processes. While existing methods usually only perform a process assessment, this work also contributes to the implementation of efficiency measures. The method is then implemented into a software tool to support companies in the continuous improvement of energy performance and to take advantage of Smart Manufacturing technologies. Through the intelligent interpretation of data, it allows identifying and characterizing the energy flow to multiple levels (e.g., machine, line, plant) and detecting its value-added component. Moreover, it allows to suggest corrective action to eliminate wasteful activities and reduce non value-added activities. The research contribution lies in a method and tool that contain metrics to identify inefficiencies using the lean approach, logics and algorithms to generate knowledge about the process efficiency status, and decision-making algorithms to appropriately suggest energy efficiency measures.

The validation in two different case studies has highlighted how the method and tool support all stakeholders in the assessment of process energy efficiency. In both case studies, they have supported the analysis and improvement process, leading to a considerable increase in efficiency and energy saving. Results demonstrate the usefulness of the proposed tool as a support for energy management toward the maximization of the manufacturing system energy efficiency and minimization of correlated environmental impact.

Sommario

Il cambiamento climatico rappresenta la sfida principale per la società del 21° secolo. L'ultimo rapporto dell'IPCC (2018) evidenzia che l'aumento delle emissioni globali di gas serra sta alterando rapidamente il clima e afferma che, se non si interviene, il cambiamento climatico influenzerà profondamente le future opportunità di sviluppo. Il settore industriale, che rappresenta circa un terzo dell'uso finale globale di energia e il 40% delle emissioni globali di CO_2 legate all'energia, potrebbe dare un contributo significativo in questo senso.

La ricerca e l'innovazione per le fabbriche del futuro non rappresentano solo una questione di sviluppo e integrazione di nuove tecnologie, ma anche una sfida per rendere la produzione meno dipendente dall'energia. L'efficienza energetica rappresenta un'azione importante per mitigare gli impatti ambientali dei processi produttivi, ed è il primo passo verso l'implementazione di una produzione sostenibile.

L'obiettivo di questa tesi è sviluppare un metodo per supportare le aziende nel miglioramento dell'efficienza energetica nei processi produttivi. Sebbene i metodi esistenti spesso eseguano solo un'analisi del processo, questo lavoro contribuisce anche all'implementazione di misure di efficienza. Il metodo è poi implementato in uno strumento software per supportare le aziende nel miglioramento continuo delle prestazioni energetiche e per sfruttare le tecnologie della Smart Manufacturing.

Attraverso l'interpretazione intelligente dei dati, consente di identificare e caratterizzare il flusso di energia a più livelli (es. macchina, linea, impianto) e di rilevarne la componente a valore aggiunto. Inoltre, permette di suggerire l'azione correttiva per eliminare le attività dispendiose e ridurre le attività non a valore aggiunto. Il contributo della ricerca è dato da un metodo e uno strumento che contengono metriche per identificare le inefficienze utilizzando l'approccio lean, logiche e algoritmi per generare conoscenza sullo stato di efficienza del processo e algoritmi decisionali per suggerire appropriate misure di efficienza energetica.

La validazione in due diversi casi studio ha evidenziato come il metodo e lo strumento supportino tutti gli stakeholder nella valutazione dell'efficienza energetica del processo. In entrambi i casi studio, hanno supportato il processo di analisi e miglioramento, portando ad un notevole aumento dell'efficienza e del risparmio energetico. I risultati dimostrano l'utilità dello strumento proposto

come supporto per la gestione energetica verso la massimizzazione dell'efficienza energetica del sistema produttivo e la minimizzazione dell'impatto ambientale correlato.

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Chapter 1

Introduction

1.1 Motivation

Climate change is the main challenge for the 21st century society. At 2015 United Nations Climate Change Conference (COP 21) held in Paris, all world nations signed a benchmark agreement to address climate change and to increase the actions and investments needed for a sustainable low-carbon future. The *Paris Agreement* aims at holding global warming to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5°C. It also aims to increase the resilience of parties to the negative impacts of climate change and to make investments coherent with a low greenhouse emission development model (UnitedNations, 2015a).

Nevertheless, the agreement does not bind the parties to the implementation of the programmes and would not effectively address climate change. The programmed national actions will collectively reduce greenhouse gas emissions compared to current policies, but still imply a median warming of $2.4 \div 3.1$°C by 2100, far from the target (Tracker, 2015; Rogelj et al., 2016) (Figure 1.1).

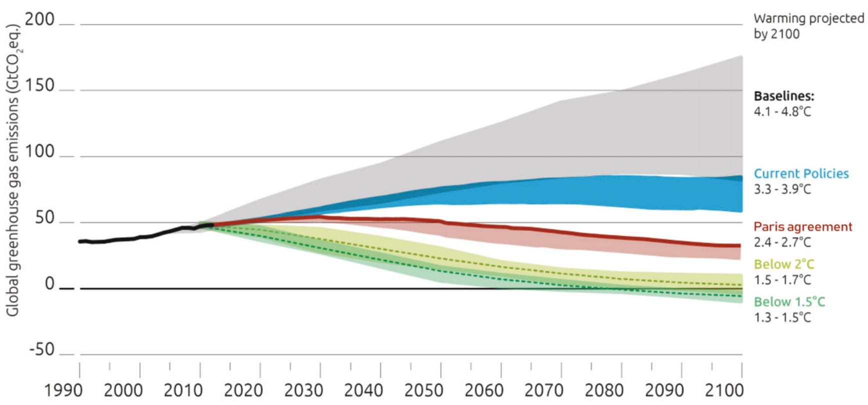


Figure 1.1: Emissions pathways and projected temperatures in 2100 under current policy and pledge scenarios (Tracker, 2015)

The latest report by the UN Intergovernmental Panel on Climate Change (IPCC) states that if nothing is done, the climate change will deeply influence future development opportunities, i.e., people's lives, economic, social and institutional systems and ecosystems in all parts of the world (IPCC, 2018). The report highlights that the increase in global greenhouse gas emissions is rapidly altering the climate. The average global temperature will reach the crucial threshold of 1.5°C above pre-industrial levels as early as 2030, intensifying desertification, reducing food production, increasing sea levels and resulting in extreme climatic events (Figure 1.2).

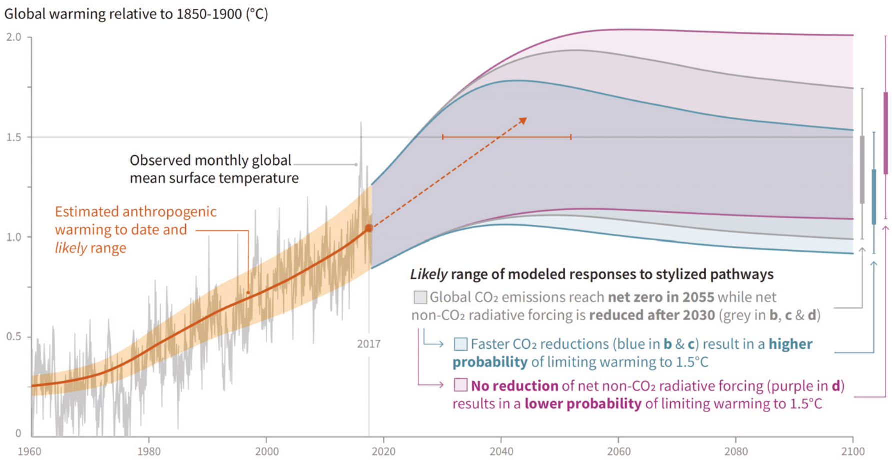


Figure 1.2: Observed global temperature change and modelled responses to stylized anthropogenic emission and forcing pathways (IPCC, 2018)

The warnings of IPCC researchers are due to the increase of CO_2 emissions which reached 32840 Mt after some years of stagnation (i.e., 1.3% over 2015). (Figure 1.3). Also global primary energy demand increased by 1.9% in 2017, the largest annual growth since 2010 and well above those of 2015 and 2016. Several factors contributed to the rebound in global energy demand and CO_2 emissions in 2017. The most notable is the global economic growth which rose from 3.1% in 2016 to 3.7% in 2017 and occurred in all major economies (IEA, 2018).

In this context, industrial manufacturing is the largest end-use sector (more than 30% of the total) in terms of both final energy demand and greenhouse gas emissions (Zhou et al., 2016). Direct industrial CO_2 emissions currently represent approximately 25% of the total energy-related and process CO_2 emissions and have increased at an average annual rate of 3.4% between 2000 and 2014, much faster than the rate of increase in total CO_2 emissions (Hoesly et al., 2018) (Figure 1.3).

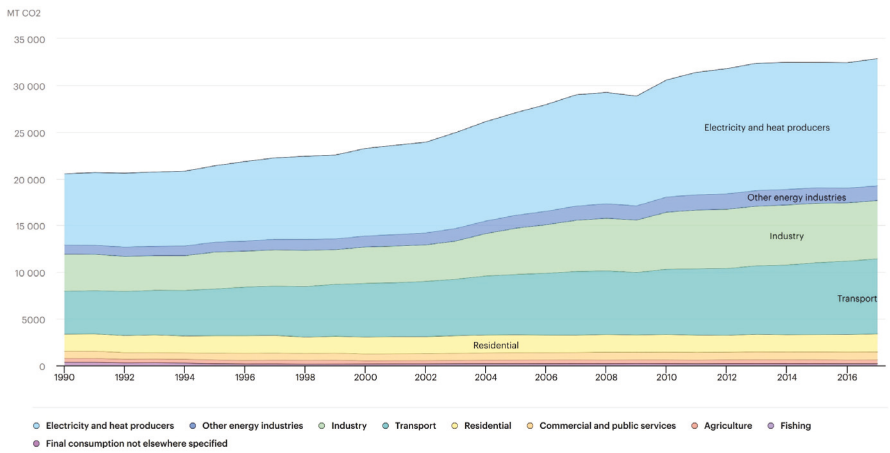


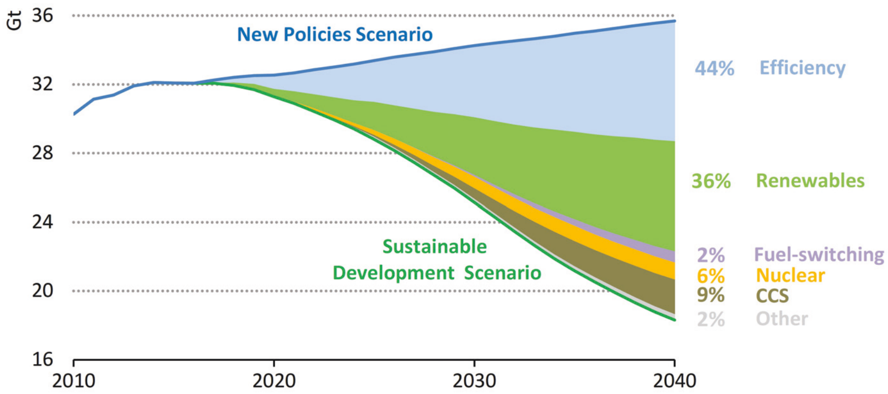
Figure 1.3: Trend of global CO_2 emissions by sector (IEA, 2019)

Notwithstanding its great environmental impact on ecosystems, the industrial sector plays a decisive role within the global economy. Manufacturing, in addition to providing the necessary and desired goods of the population, employs a significant part of workers (i.e., one-quarter) and contributes to the development of community welfare and the economy (UnitedNations, 2015b).

For this reason, the 2030 UN Agenda for Sustainable Development has placed sustainable production among the seventeen goals for building a better world (UnitedNations, 2015b). In fact, only through the development of non-polluting production systems and processes and the consumption of limited quantities of resources, is it possible to combine environmental, economic and social sustainability (Seliger et al., 2008). The ambition is "*doing more and better with less*", which means increasing net welfare gains from economic activities by reducing resource use, degradation and pollution along the whole life-cycle, while increasing quality of life (UnitedNations, 2015b).

Energy efficiency is inevitably linked to this challenge: it represents an important action for mitigating the environmental impacts of manufacturing processes, and it is the first step towards the implementation of sustainable production (IPCC, 2018).

The work of the IEA (2018) demonstrates that the introduction of efficiency measures represents a significant contribution to the CO_2 emission reduction. They highlighted that, if combined with other measures, efficiency will achieve over 40% of the carbon emissions reductions required to meet global climate change mitigation goals (Figure 1.4).



(Note: New Policies Scenario simulates the scenario under current and planned policies, the Sustainable Development Scenario relies on all of net-zero targets being achieved on schedule and in full)

Figure 1.4: Global CO_2 emissions reduction by measures in the Sustainable Development Scenario relative to the New Policies Scenario, 2010-2040 (IEA, 2018)

The report identifies the potential for industry to produce nearly twice as much value per unit of energy use in 2040, compared with current levels. The less energy-intensive sectors (e.g., automotive, food and beverage and textiles manufacturing) account for the largest percentage of the potential energy savings for industry in 2040 (i.e., 70%), thanks to efficiency improving by over 40%. In the more energy-intensive sectors the improvement in energy efficiency is smaller, such as in cement industries that could improve by only 10%.

The extension and strengthening of standards for key industrial equipment (e.g., MEPS and the last class of IE4 Super Premium Efficiency for electric motor) are already leading to significant efficiency gains especially in less energy-intensive industrial sectors (IEA, 2018). However, end-use device inefficiencies are mainly linked to incorrect device management (Johansson and Thollander, 2018).

These inefficiencies can be overcome through the development of methods and tools to support the implementation of energy management systems and to assist the implementation of measures that increase the efficiency of the production system. Methods and tools are needed to help the systematic planning, analysis, control, monitoring and improvement of energy use and efficiency. They are effective in developing better practices across large parts of industry that may not have the expertise or incentive to focus on efficiency as much as energy-intensive sectors.

1.2 Objectives

The main objective of this work is to develop a method that supports the increase of energy efficiency in industry. It aims to matching the necessity to make the industrial process more sustainable with the potential of factory digitalization.

In recent years, the amazing advances in data, analysis and connectivity are enabling a range of new digital technologies to be applied in the industry such as IoT, big data analysis, cloud computing and 3D printing. A new production model, known as Smart Manufacturing, has emerged. This digital revolution offers many opportunities for energy efficiency improvements, such as for example, the control of the interconnected robots by algorithms to reduce their energy consumption, or the application of new software tools to optimize and adapt the business process. However, the focus is more on proposing more efficient designs of the individual components of manufacturing systems, than on the design of management and control systems of energy consumption for these systems.

The aim is to develop a method and a tool to improve the efficiency of manufacturing systems through the intelligent interpretation of data and to suggest corrective actions. Through the method and tool, the process manager or energy manager will be able to answer the following questions:

- *When, where and why does inefficiency occur?*
- *Who is responsible for it?*
- *Which are the most suitable improvement strategies?*

The work is part of the research topic of energy management in smart manufacturing systems with a focus on the supporting tools and methods for energy efficiency assessment. The method and tool will support the industrial companies:

– to monitor and analyse the energy consumption of a factory and its manufacturing processes and they represent the first step towards increasing energy efficiency;

– to cope with the knowledge and organizational barriers of implementing energy reduction measures;

– to identify improvement opportunities and to track the effects of their decisions on energy use;

– to measure, control and improve energy efficiency in production systems;

– to increase the transparency of a system's real time energy consumption and improve energy awareness. They will allow analysing different aspects of production (e.g., technologies, raw material, time, etc.) and assessing their effects on energy efficiency.

In addition, the development of a method and tool to improve energy efficiency and proper energy management will enable manufacturing companies to satisfy the ever stricter environmental regulations about CO_2 emissions and the increasing awareness of customers that are requiring greener and more sustainable products, as well as to maintain competitiveness by reducing energy costs.

To achieve the above-mentioned challenging objective, a *Research Plan* is defined. The final aim is to organize all the foreseen activities in a clear workflow, to obtain relevant results, which are innovative from the scientific point of view and attractive for the industrial world. Defining the research plan meant planning the activities and selecting both theoretical and empirical research methods and settings.

The first step of the research process is entirely dedicated to the scenario analysis in order to understand the context in which this research work is positioned. The first activity focuses on identifying the problem in a practical context and understanding the research framework. Theoretical knowledge of the basic and formal sciences is analysed. Theories, approaches, and hypotheses are identified and examined with regard to the specific problem in order to create a research background. Then, existing normative and legislations, both at European and International levels, are examined. This is essential to understand the opportunities and limitation, in order to correctly focus the development activities.

Next, an analysis of the state of the art of scientific publications is conducted. This phase allows to identify the methodologies for energy management in production systems, the tools already developed, as well as the main lacks and the aspects that needed to be explored and improved. Moreover, the comparison between existing research contributions helps to identify relevant concepts that can be integrated into the research work development.

A fundamental step is certainly the deep investigation of the industrial processes. In parallel with the state-of-the-art analysis, the problem is analysed from the company's point of view. Direct and indirect analyses allow to better understand their knowledge on the energy efficiency and energy management issues, their modus operandi, their main lacks and limitations, and their needs on this issue. The study of the industrial world allows to converge toward solutions, which are feasible from the technical point of view, and aligned with their needs.

The second step concerns the development of the method and the tool. Activities begin with the definition of the methodology based on the limitations and requirements that emerged from the scenario analysis. A continuous update of the scientific and technological state of the art is also carried out to guarantee a high degree of novelty of the results. Then, the method is implemented in a tool to support companies in the continuous improvement of energy performance. During the development step, preliminary validation tasks are carried out to constantly check the usefulness and effectiveness of the proposed method and tool.

After the development of the method and tool, these are tested in a practical context as part of the last step. The tests focus on the applicability of the method and tool, i.e., whether the research result achieves a practical benefit. The validation is performed on real complex case studies and allowed to verify the applicability and effectiveness of the proposed energy management tool.

1.3 Thesis overview

The structure of the thesis follows the research plan. It contains the main steps to investigate the state of the art from both a practical and scientific point of view. Then, the main limitations and requirements are deduced; and based on these, the method and tool are developed and evaluated.

As part of this first chapter, the motivation towards the topic is presented and research objectives are deduced. Based on these goals, a corresponding research plan is established.

Chapter 2 examines the general context in which the research work is inserted. In the first part, it explains the meaning of sustainable manufacturing and smart manufacturing. Then, it addresses the energy use in manufacturing industry. It explores drivers that promote the need to increase energy efficiency from an economic, ecological and social perspective, as well as the international and European legislative environment. In addition, obstacles and limits towards the implementation of energy efficiency strategies are investigated with the aim of considering these as starting points for the development of the method and tool. In the last part of the chapter, it investigates the scientific literature regarding energy assessment methods and tools. A critical review of the most important research works on these topics is presented to understand the scientific basis for this research work. The evaluation allows to recognize the most important gaps to bridge in order to make the methodology and tool innovative and, at the same time, usable in real industrial contexts.

The third chapter presents the *Method to assess the energy efficiency of manufacturing systems* which aims to map and classify activities and related energy consumptions according to lean philosophy principles. Based on the outcomes from the previous chapter, requirements for the method are formulated. Next, the framework for the method is presented and the relevant components of the research contribution are discussed. The activities to be followed for each step of the method are explained in detail. In addition, the new indicators and algorithms that support the identification of critical issues and guide decision making during the implementation of improvement strategies are described.

Chapter 4 illustrates the implementation of the method defined in the previous chapter in a tool. It describes the *smart Energy Value Mapping* (sEVM) tool that aims to support companies in the continuous improvement of energy performance. After a brief explanation of the system architecture, it presents the sEVM tool framework. The data structure, databases, logics and algorithms and, finally, the user interface are described in detail.

The fifth chapter addresses the validation of the tool in two real case studies with regards to the criteria of relevance and usefulness. The case studies are explained through the description of the production process, the tool implementation and the results obtained after a 4-month experimentation period. At last, the overall results are described, allowing to validate the methodical approach and the tool against the research gap.

Finally, chapter 6 presents conclusion and discusses the achieved findings outlining strengths and weaknesses of the proposed method and tool. Suggestions for future directions of research are also provided to stimulate the continuation of the work in the context of energy management issues.

Chapter 2

Research background

2.1 Smart sustainable manufacturing

The manufacturing industry is the core element in the transition of society towards a more sustainable model. The automation combined with advanced production technologies will help the transition of manufacturing practices to the circular economy (WMF, 2018). As a result, in recent years a new manufacturing model that combines the concepts of sustainability and smart has emerged.

The aim of the smart and sustainable manufacturing of the future is to facilitate clean and competitive production systems independently of plants' site or size, and to identify chances based on sustainability issues to grow.

2.1.1 Sustainable manufacturing

The concept of sustainable development was first defined in the 1987 Brundtland Report as *"development that meets the needs of the present without compromising the ability of future generations to meet their own needs"* (Brundtland et al., 1987). In 2005 the UN World Summit extended this concept by stating that three interdependent and mutually reinforcing pillars exist to support it: economic development, social development, and environmental protection (UnitedNation, 2005). These three interdependent pillars have been pointed as the triple bottom line (people, profit and planet) that allow to consider the world in a holistic way (Figure 2.1) .

Several definitions of sustainable manufacturing are in use and all concern the environmentally responsible production and use of manufactured goods. In the UN 2030 Sustainable Development agenda, it has been defined as *"promoting resource and energy efficiency, sustainable infrastructure, and providing access to basic services, green and decent jobs and a better quality of life for all"* (UnitedNations, 2015b). Although widely accepted, this definition is not an operational one for business and engineering decision makers in manufacturing. A more operative definition has been provided by the U.S. Department of Commerce, which has defined sustainable development as *"the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound"* (Department of Commerce, 2012).

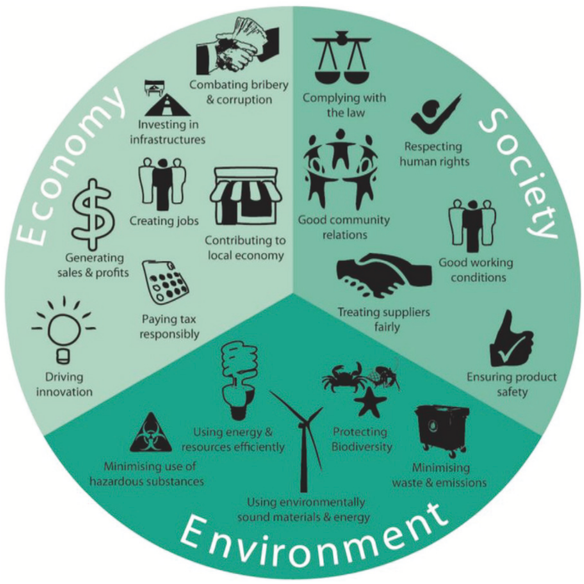


Figure 2.1: Three-dimensional aspects of sustainable manufacturing (OECD, 2011)

The review work of Moldavska and Welo (2017) has shown that there is no uniform consensus among scholars on the true meaning of the sustainable manufacturing, as evidenced by the numerous identified definitions. The most commonly used definition is the one proposed by U.S. Department of Commerce: 63% of the analysed articles cite or slightly rephrase this definition (i.e., 119 papers on a total of 189). Furthermore, there seems to be an inconsistency in the general understanding of the concept since only 11 of the 67 subcategories are shared (i.e., product, resources, energy consumption, production process, design process, natural environment, community, safety, workers and customers).

Sustainable manufacturing has not a single definition and passes through different topics, but nevertheless it is based on the principle that humans depend on the natural environment for survival and well-being, and that humans and nature can exist in productive harmony. It is therefore essential that manufacturing should consider not only economic sustainability, but also environmental and social sustainability.

A growing number of enterprises implement the principles of "sustainability" in order to improve performance and reduce their resource footprint. In detail, the main reasons why companies are pursuing sustainability are *(a)* maximize efficiency by reducing operating costs and waste, *(b)* meet new customers and increase competitive advantage, *(c)* preserve and reinforce the brand, *(d)* enhance the company's long-term profitability and success and *(e)* respond to regulatory constraints and opportunities (EPA Environmental Protection Agency, 2006).

2.1.2 Smart manufacturing

In parallel with the spread of the sustainable manufacturing topic, a new paradigm for the production process is becoming evident. After the industrial revolutions of the 18th century, the end of the 19th century and the 1970s, industrial production is undergoing another fundamental transformation (Figure 2.2). This (fourth) revolution is based on the creation of a smart and connected production systems.

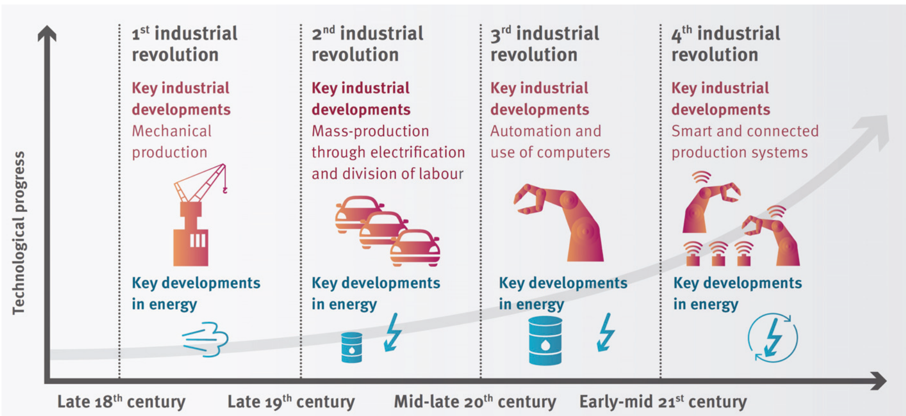


Figure 2.2: The four industrial revolutions (UNIDO, 2017)

This new approach was first defined in Germany as "Industrie 4.0" by the working group chaired by Siegfried Dais as *"networks of manufacturing resources (manufacturing machinery, robots, conveyor and warehousing systems and production facilities) that are autonomous, capable of controlling themselves in response to different situations, self-configuring, knowledge-based, sensor-equipped and spatially dispersed and that also incorporate the relevant planning and management systems"* (Kagermann et al., 2011).

The new manufacturing model, called "Smart Manufacturing", is built on the use of technical advances in information and communication technologies (ICT) and their increasing integration into production systems through customised, progressively smaller, safer, more robust components. Mechatronic systems will be enhanced regarding additional communication ability (intelligent sensor systems, actuators, interaction with the environment) and (partly) autonomous performance. Machinery and equipment will thus be able to reconfigure and optimise performance autonomously (e.g., independent performance planning according to the environment; learning new performance modes and strategies).

The new model will be based on the Cyber-Physical Systems (CPS): physical and virtual, local and global systems, horizontally and vertically connected, with partial or complete autonomy able to control in real time the production process and support the cooperation between human and system (Figure 2.3). They involve all systems (i.e., production, logistics, engineering, coordination and management processes) as well as Internet services, gather physical data through sensors and influence the processes. They are interlinked by digital networks, use data and services that are available worldwide and incorporate multimodal human-machine interfaces (Geisberger and Broy, 2012).

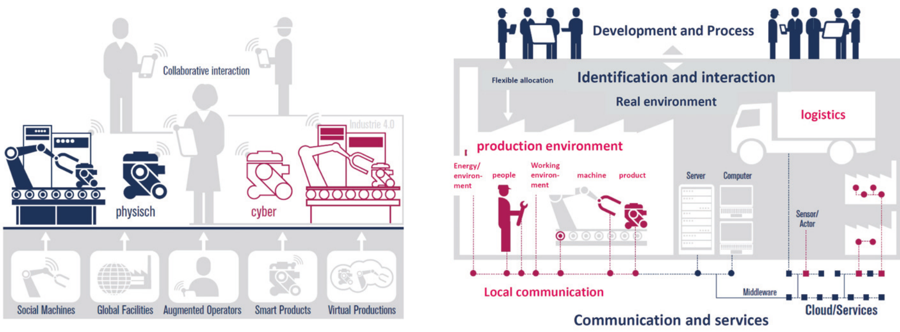


Figure 2.3: Industry 4.0: CPS, interactions and networking with its environment (Kagermann et al., 2011)

This paradigm is also based on the Internet of Things (IoT) and the Internet of Services (IoS): a flexible and consistent networking of the data sources on the basis of a services model (Figure 2.4). In detail, the IoT provides connectivity to a factory site, the service platforms connect IoT and IoS while executing CPS functions and finally the IoS connects applications to business processes and applications for each area (Kang et al., 2016).

In 2015, the the U.S. National Institute of Standards and Technology (NIST) defines Smart Manufacturing as *"fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs"* (NIST, 2015).

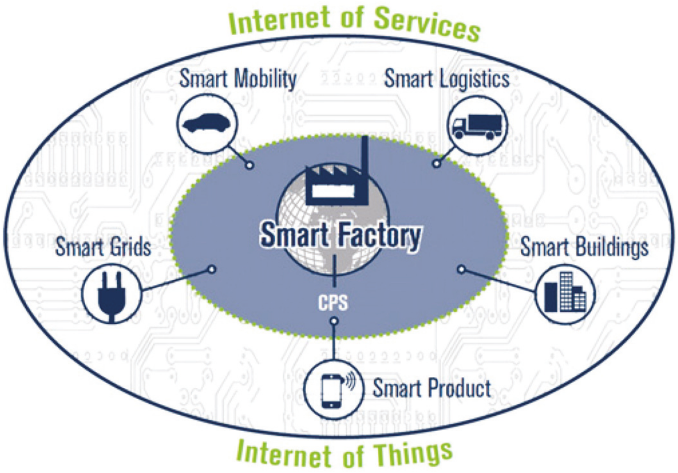


Figure 2.4: Industry 4.0 as part of the IoT and IoS (Kang et al., 2016)

Also in this definition, the novel manufacturing paradigm is intended as a combination of innovative technologies that can react in real time to changes in production systems and promote real time decision making through the introduction of ICT and the interaction between humans, technology and information.

The review of Kang et al. (2016) shows how Smart Manufacturing can be successfully realized through a balanced development and application of eight key technologies. The major key technologies related to Smart Manufacturing are:

- CPS: they are systems of computational entities that collaborate in close connection with the surrounding physical world and its processes, providing and employing data-accessing and data-processing services. This technology is central to the development of Smart Manufacturing, and it is being studied in close relationship with such technologies as cloud, IoT and big data.

- Cloud Manufacturing: it is based on cloud computing technology applied to the industry, and is a customer-centric production model. It works through the sharing of data, products and services with the aim to reduce costs, improve efficiency and optimize resources.

- Big Data Analytics: it is a term used to describe the analysis of data sets characterized by high volume, high speed and high variety through advanced analytical tools. Data processing enables the identification of patterns, trends and relationships useful to create relevant statistics that allow more informed decisions to be made on economic, environmental or social issues.

- IoT: it describes a network of interconnected so-called smart objects, embedded sensors and miniaturized computers, able to sense their environment, process data, and engage in machine-to-machine communication. IoT supports integration between physical real world and computer-based systems, and brings various effects such as improved productivity or economy in manufacturing.

- Smart Sensor: it is the most relevant technology at device or hardware layer in the realization of IoT, CPS and Smart Manufacturing as it represents the core element for real time data collection and control.

- Additive Manufacturing: it is a production method which is based on the conversion of a 3D model into a physical object, by bonding or joining materials through light, ultrasonic vibration, laser and electron beam. In comparison with traditional technologies, it reduces the waste of material and resources and introduces greater production flexibility. However, this technology needs to be developed to improve its performance, reduce costs and applicability.

- Energy Saving: it is an important element for the realization of Smart Manufacturing as it increases the sustainability of production processes. It is based on the monitoring of energy consumption through the use of Smart Sensors, Big Data Analytics, IoT. It allows to increase efficiency and to support decision makers in planning and managing the production process.

- New Human-Machine Interactions: they represent new ways to make information available and are based on Virtual Reality and Augmented Reality technology. They can be applied to every area of production, from product/process design to layout planning and factory assets. One big potential is seen in the service sector, for example in maintenance where such technologies allow operators to connect with service experts from the producing company, allowing them to jointly inspect the product and develop feasible maintenance solutions, without forcing experts to physically travel to the customer.

2.2 Energy efficiency in industry

Energy efficiency represents an important measure for mitigating the environmental impacts of manufacturing processes, and it is the first step towards the implementation of sustainable production (IPCC, 2018).

It contributes to all three aspects (triple bottom line) that are considered in sustainable production framework (Bunse et al., 2011) (Figure 2.5):

- It allows to improve the economic sustainability of a manufacturing process through the reduction of energy and resource purchase costs, the access to public funding (e.g., green certificates) and an economic benefit resulting from the improved productivity and the lower dependence on the variability of energy costs.

- From the environmental point of view, the improvement of energy efficiency would reduce emissions of CO_2 and other harmful gases and limit the impact on resource scarcity.

- Finally, energy efficiency contributes to social aspect of sustainability through better energy awareness of customers and workers and a better corporate image .

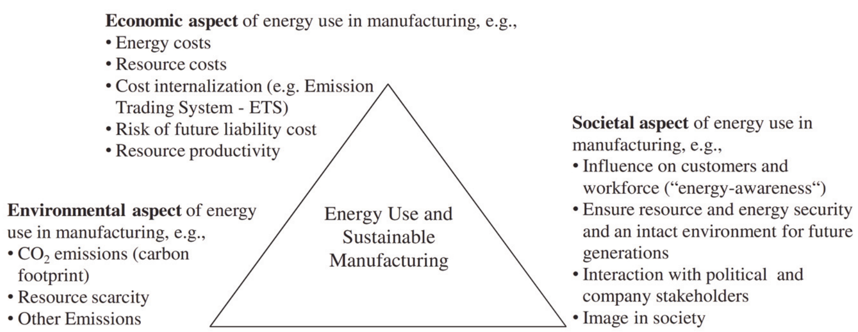


Figure 2.5: Energy efficiency contribution to the three main dimensions of sustainable manufacturing (Bunse et al., 2011)

Energy efficiency is also essential from a company's point of view, as rising energy prices and costs for greenhouse gas emissions affect a company's competitiveness on the market. The main driving force for improved energy efficiency is the adoption of national and international regulations and standards that recommend, and sometime prescribe, a better company energy management in order to reduce its consumption. Other drivers are the increasing costs for purchasing energy and a greater customer awareness of sustainable, energy-efficient products and services.

However, companies are faced with barriers and limitations that hinder the implementation of energy efficiency measures.

Barriers are defined as the main inhibitors for a company on the way to implement environmentally and economically efficient measures (May et al., 2017). They vary according to the industrial sector, companies' characteristics and external pressures. Nevertheless, there are some common barriers to the different industrial sectors such as 'access to capital', 'lack of time or other priorities', 'technical risks' and 'information-related obstacles' (Johansson and Thollander, 2018).

The empirical results about these barriers underline how the obstacles related to information and organisation could be overcome by developing new methods and tools. These should support the implementation of efficiency policies without requiring specialist knowledge and with a manageable effort.

2.2.1 Definition

Energy efficiency is defined as the ratio of any output to the necessary input of a system (Equation 2.1). This description is very generic and is applicable to each company and can mean different things at different times and in different places or circumstances.

$$Energy\ Efficiency_{general} = \frac{output\ of\ performance,\ good,\ service\ or\ energy}{input\ of\ energy} \tag{2.1}$$

In the context of a manufacturing process, energy efficiency is defined as the ratio of the useful output to the total energy input (Equation 2.2). Increasing energy efficiency therefore means increasing the outputs with no or proportionately less increase of the input energy or reducing energy consumption while keeping output (at least) at the same level.

$$Energy\ Efficiency_{manufacturing} = \frac{useful\ output}{energy\ input} \tag{2.2}$$

Careful attention must be paid to the boundaries of the system analysis, as well as of the different possible input and output variables. For example, production could be expressed in terms of produced amounts (e.g., pieces), masses (e.g., kilograms) or revenues generated (e.g., euro, US dollars). Energy input could be measured, for example, by energetic value (e.g., kWh), energy costs (e.g., euro, US dollars) or environmental impact (e.g., CO_2 emissions).

Energy efficiency also depends on the level of analysed manufacturing. Through a hierarchical approach it is possible to distinguish three macro levels that constitute a production company: machine, production line and plant (Figure 2.6).

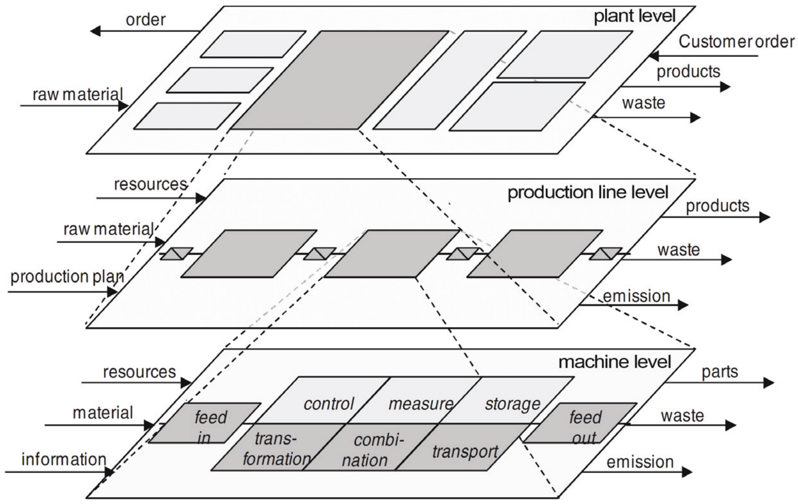


Figure 2.6: Hierarchical schematisation of the manufacturing process (adapted from Herrmann et al. (2007))

At the lowest level, production processes are performed by machine tools, which only do one kind of operation over a piece. From the review of Zhou et al. (2016), the energy efficiency of machine refers to the relationship between the effective energy and the energy consumed by the device in a finite time. It is expressed as the ratio of machining power to the machine input power.

Then, there is the level of the production lines where more machines and auxiliary devices are aggregated for the production of a piece. At both machine and line level, auxiliary devices are required to ensure proper machine operation and the adequate supply of resources to the machines.

Finally, the highest level is represented by the plant where all the machines, production lines and TBS involved in both valuable and non-valuable activities are considered.

Both at line and plant level, the definition of energy efficiency is based on the kind of case study and the type of assessment. Due to the existence of complex relationships among machines and their different configurations, peripheral devices and the working environment, Equation 2.2 is employed and then adapted according to the application.

2.2.2 Driving forces for improved energy efficiency

From the companies' points of view, energy efficiency is becoming an important theme in production management due to three important drivers: rising energy prices, new environmental regulations (with their associated costs for

CO_2 emissions) and greater customer awareness of sustainable, energy-efficient products and services (Bunse et al., 2011).

Energy cost

Energy consumption represents an important share of total production costs for industrial companies. Statistically they amount between 1% and 10% of the total production costs (European Commission, 2018), where total (operating) production costs are equal to personnel costs and total purchase of goods and services, including energy (Figure 2.7).

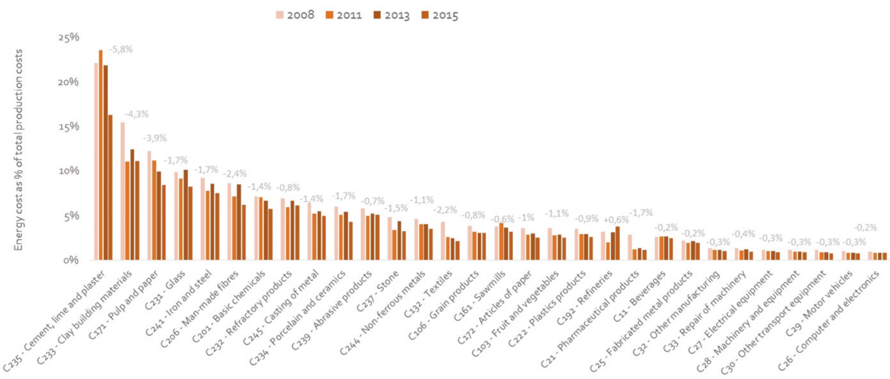


Figure 2.7: Average energy cost as % of total operational production cost for manufacturing sectors and change 2008-2015 (European Commission, 2018)

There are some industrial sectors that exceed 10% (i.e., Cement, lime and gypsum, Clay building materials and Paper production) while for the other sectors, energy costs range from 2-10% of total (operating) production costs. For less energy-intensive manufacturing sectors (i.e., Computers and electronics, Motor vehicles and Other transport equipment), energy costs are typically only 1-3% of total operating (production) costs.

Although energy costs are averagely low compared to personnel costs or other factors, they are still an important driver to increase the company's profitability. This is particularly important when it is assumed that energy prices will rise in the future (European Commission, 2019). In recent years, rising oil and gas prices have slightly increased the cost of energy bills for companies. Nevertheless, the latest forecasts show a considerable growth of the cost of energy in Europe in 2030 (Figure 2.8).

Finally, the structure of energy consumption within a factory is highly dependent on the industrial sector (Figure 2.9). In general, the continuous manufacturing industry is characterised by a prevalent consumption of thermal energy,

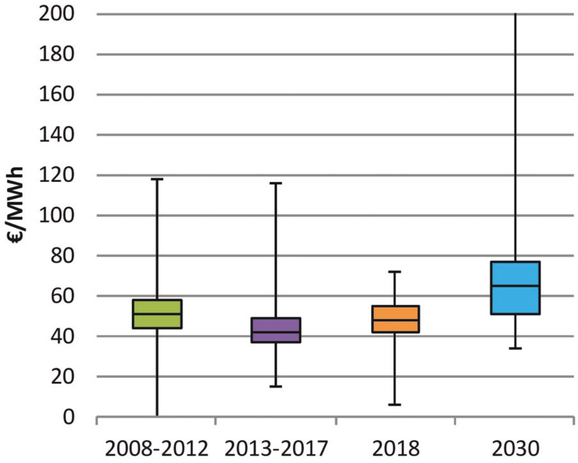


Figure 2.8: Energy price trends in EU28 (European Commission, 2019)

often produced with fossil fuels (e.g., in the manufacturing of glass, refractory products, clay building materials, porcelain and ceramics). The discrete manufacturing industry, characterised by the production of single items, has instead a prevalent consumption of electrical energy, as in the sectors of non ferrous metals, fabricated metal products, computer and electronics, motor vehicles, other manufacturing.

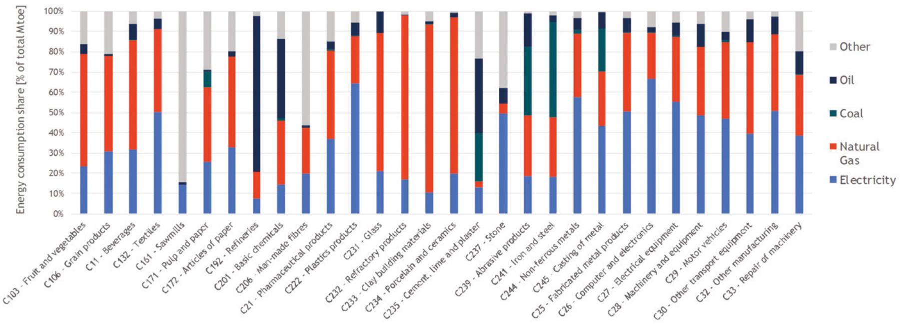


Figure 2.9: Breakdown of the energy consumption per energy carrier EU, 2008-2015 averages (European Commission, 2018))

Norms and standards

Another driver for improving the energy efficiency of industries is the national and international norms and standards.

The main international standard on energy management and energy management systems is ISO 50001:2018 (ISO, 2018). It was released in June 2011, replacing the European standard EN 16001:2009 and then, revised in August 2018. The ISO 50001 describes the framework for implementing an energy management system within an organization. It has the same structure as ISO 9001:2008 standard for quality management and ISO 14000:2004 standard for environmental management.

The aim of the standard is to promote the best practices of energy management and to improve energy control in the context of greenhouse gas emission reduction initiatives. In detail, this standard specifies energy management system (EnMS) requirements, upon which an organization can develop and implement an energy policy, establish objectives, targets and action plans which take into account legal requirements and information related to significant energy use. The standard is based on the plan-do-check-act (PDCA) cycle which leads to continuous improvement of energy performance:

- Plan: establish the objectives, performance indicators and benchmark values. Plan data collection and conduct energy review;

- Do: define the resources to be allocated, design and implement the energy management action plans;

- Check: monitor the energy consumption, measure the processes and parameters that determine energy performance and compare the results with the established targets;

- Act: take action to continuously improve energy performance and the energy management system.

The certification of conformity of an EnMS with respect to this international standard is non-binding. The standard establishes procedures to manage the energy factor in a systematic way through periodic audits and corrective action planning. Companies can thus keep the efficiency of the production process under control and achieve energy and economic savings. In addition, the certification to the ISO 50001 standard allows companies to access state funding of *"Titoli di Efficienza Energetica"* established in Italy by the Ministerial Decree of 20 July 2004.

By the end of 2017 the number of world certifications to ISO 50001 had reached nearly 23000, a 13% increase from 2016 (Figure 2.10). Nevertheless, there was a marked slowdown in the growth of total certifications observed in previous years. The main factors that contributed to the slowdown in 2017 were the 8% reduction in German certifications and the companies' lack of understanding of the real potential of an EnMS and the benefits that can be obtained (IEA, 2018).

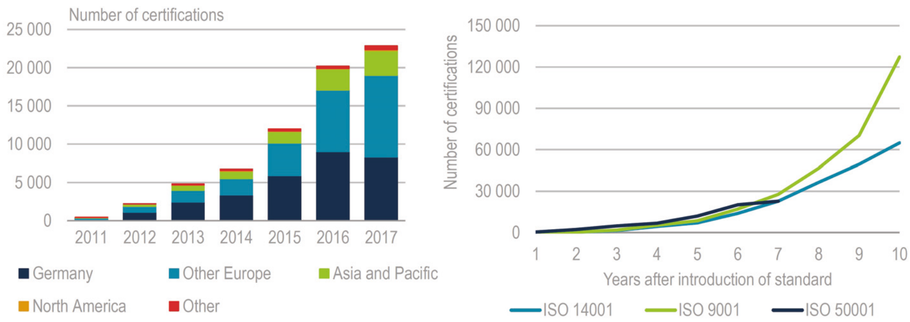


Figure 2.10: ISO 50001 certifications 2011-17 (left) and certification progress compared with other management standards (right) (IEA, 2018)

The ISO 50001 only establishes generic procedures for structuring the organisation and processes. It can be considered as a management instrument on a general level. It does not provide support about how the identification of energy efficiency measures may be conducted. Moreover, the standard is poorly applicable for SMEs due to the complexity of the procedures and the effort required.

The ISO 50001 is strictly linked to other standards that define and examine the various issues related to energy management. The ISO 50001 is the core of the ISO 50001 family, but there are also the following standards:

- ISO 50002:2014 – Energy audits – Requirements with guidance for use (it touches on matters related to energy diagnosis).
- ISO 50003:2014 - Energy management systems — Requirements for bodies providing audit and certification of energy management systems.
- ISO 50004:2014 - Energy management systems — Guidance for the implementation, maintenance and improvement of an energy management system.
- ISO 50006:2014 - Energy management systems — Measuring energy performance using energy baselines (EnB) and energy performance indicators (EnPI) — General principles and guidance;
- ISO 50007:2017 - Energy services — Guidelines for the assessment and improvement of the energy service to users (it involves activities related to energy services).
- ISO 50008:2014 -Energy management and energy savings — Building energy data management for energy performance — Guidance for a systemic data exchange approach (it relates to energy management in commercial buildings).

- ISO 50015:2014 - Energy management systems — Measurement and verification of energy performance of organizations — General principles and guidance (it approaches matters related to measurement and verification).

Then, there are the following standards that are commonly used in an energy review process of an industrial process:

- UNI CEI 11339:2009 - Energy management - Energy managers - General requirement for qualification.
- UNI CEI EN 15900:2010 - Energy efficiency services - Definitions and requirements. It specifies the definitions and the minimum requirements for a energy efficiency improvement service. The standard does not describe the requirements of the service provider, but identifies and describes the main stages of the process of suppling and highlights the basic requirements.
- UNI CEI EN 16231:2012 - Energy efficiency benchmarking methodology. The standard defines the requirements and provides recommendations on the methodology for energy efficiency benchmarking. The indicators may be both technical and behavioural, qualitative and quantitative, and must be focused on performance comparisons.
- UNI CEI EN 16212:2012 - Energy Efficiency and Savings Calculation - Top-down and Bottom-up Methods. The standard provides a general approach for energy efficiency and energy savings calculations with topdown and bottom-up methods. It is meant to be used for ex-post evaluations of realised savings as well as ex-ante evaluations of expected savings.
- UNI CEI EN 16247-1:2012 - Energy audits - Part 1: General requirements. It specifies the requirements, common methodology and deliverables for energy audits. It applies to all forms of establishments and organizations, all forms of energy and uses of energy. It covers the general requirements common to all energy audits, while the specific requirements are described in the following parts: part 2 for building audits, part 3 for processes and part 4 for transport.
- UNI CEI EN 16247-3:2014 - Energy audits - Part 3: Processes. It specifies the requirements, methodology and deliverables of an energy audit within a process. These consist of: *(a)* organizing and conducting an energy audit; *(b)* analysing the data from the energy audit; *(c)* reporting and documenting the energy audit findings.
- UNI CEI EN 16247-5:2015 - Energy audits - Part 5: Competence of energy auditors. It specifies the competence requirements of the energy auditor.

- UNI EN ISO 19011:2018 - Guidelines for auditing management systems. It provides guidance on auditing management systems, including the principles of auditing, managing an audit programme and conducting management system audits.

At the Italian national level, on 4 July 2014 was published the Legislative Decree n 102/14, implementing the European Directive 27/2012 on energy efficiency. The 102/2014 Decree establishes a framework of measures for the improvement of energy efficiency intended to contribute to the national objective of energy saving. The standard is applied to large and energy intensive companies with the requirement to carry out an energy audit by 2015 and repeat it every four years.

The companies subject to duty are: *(a)* companies with strong consume of energy (*'energivorous'* regarding DM 05.04.2013) indipendently from their dimensions. In detail, all companies for which, in the year, have been verified both conditions: they have used, for the performing of own activity, at least 2,4 GWh of electrical energy and the relation between the effective cost of the energy used and value of turnover shall not result less than 3% (DM 05.04.2013). *(b)* Companies that employees more than 250 people or that has a turnover that exceeds 50 millions euro and that has an annual balance exceeds the 43 millions euro.

Audit shall be carried out by entities or qualified experts certified by accredited bodies: energy service company (ESCo) under UNI CEI 11352:2014, experts in energy management (EGE) certificates UNI CEI 11339:2009 and energy auditor under UNI 16247–5. The energetic audit is carried out on the basis of minimum standards set up by the norm UNI CEI EN 16247-1:2012 and contains the following information:

- analysis of energy consumes (electric, thermic, gas, etc.);
- definition of consume profile of the company;
- definition of efficiency index of the single functional areas and company itself;
- indication of the solutions for the improvement of energetic efficiency.

2.2.3 Limits to the energy efficiency implementation

Despite the various drivers, enterprises face barriers that hinder the implementation of energy efficiency measures. They may take many forms and are determined by the characteristics of the enterprise (size and structure) and the business environment.

Barriers are generally classified into three broad categories: economic, behavioural and organisational factors. For the industries, IPCC (2001) has proposed to distinguish four main groups of barriers, namely, lack of information, limited availability of capital, lack of skilled personnel and a bundle of other barriers. These wide groups were subsequently further differentiated by Sorrell et al. (2004) and Schleich (2009) who categorise the barriers into six categories. They differentiate imperfect information, hidden costs, risk and uncertainty, split incentives, access to capital and bounded rationality. Trianni et al. (2016) extended this categorization and divided barriers into:

a) Technology-related: it describes the unavailability of energy efficient technologies, e.g., low diffusion of monitoring technologies and appropriate tools for analysis and evaluation.

b) Organisational: it contains all aspects of structural and procedural organisation, such as lack of human resources, complex decision-making chains or the absence of energy efficiency managers.

c) Information: it describes the lack of information within the company about energy efficiency such as the lack of transparency about energy consumption and costs/benefits of an energy efficiency measure.

d) Economic: it describes the limited availability of capital to implement energy efficiency measures. An example is the no access to capital, the high cost of implementation and the low rate of return.

e) Behavioural: it describes a company's decision-making actions such as, for example, the decision to give low priority to energy efficiency measures compared to other objectives.

f) Market: it includes market barriers such as uncertainty regarding the future of the company and the variability of energy costs.

g) Competence: it includes the lack of specialised know-how (competence) within the company

h) Awareness: it concerns the lack of awareness of managers and decision-makers towards energy efficiency issues.

i) Government/Politics: it is about national and international policy choices such as the adoption of standards and regulations or the definition of financing for energy efficiency.

Surveys conducted by Fleiter et al. (2012b) and Johansson and Thollander (2018) highlighted the main barriers to the implementation of energy efficiency measures. The two works obtained comparable results: in the former, the most important barriers are ‘high investment costs’, ‘other priorities for capital investment’ and ‘unprofitable interventions’ (Figure 2.11). In the latter, the most relevant barriers were ‘other priorities for capital investments’, ‘lack of time or other priorities’, ‘risk of production disruption’ and ‘lack of access to capital’.

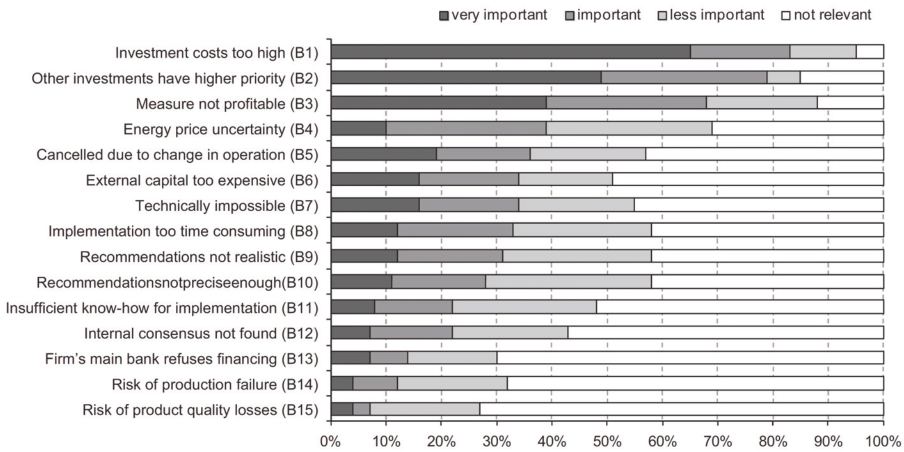


Figure 2.11: Ranking of limits to the energy efficiency implementation (Fleiter et al., 2012b)

Half of the barriers focuses on economic and organisational barriers. The second most important aspect is related to information, which includes the lack of know-how and the lack of specific knowledge for the implementation of efficiency policies.

The results of the survey demonstrate the need to provide this knowledge to industrial enterprises. In order to address organisational and information barriers, new methods and tools providing information on energy efficiency need to be developed. Through the simplification and application of supporting tools, methods can be applied with a ‘sustainable’ effort and overcome the limits of the energy efficiency implementation.

2.3 Review of energy assessment methods and tools

After the definition of energy efficiency in industry, a systematic review of scientific publications related to the supporting tools and methods for energy efficiency assessment has been carried out. The scientific articles of the last twenty years have been analysed, with a threefold purpose:

- to identify the state of the art in scientific research and its trends;
- to define the relevant concepts, themes and characteristics within the literature;
- to determine the limits of current scientific research.

The research work was conducted between September and November 2018 according to the systematic review approach. This approach, introduced by Tranfield et al. (2003), allows relevant existing studies to be identified based on a previously formulated research question. Moreover, this method minimizes the subjectivity of the author as it ensures the transparency of the results and the repeatability of the study (Denyer and Tranfield, 2009). The research consisted of looking for relevant works within the main on-line databases of scientific literature that collect academic studies published in peer-reviewed journals. The databases used for the present research were *Web of Science, Scopus* and *ScienceDirect*, which collect relevant academic articles in the fields of industrial production management and energy, as well as the engineering domains, and allow accurate and customized searches.

The main keywords for the review were identified as "*method*", "*manufacturing*" and "*energy assessment*". They have been selected to detect the scientific papers focused on energy efficiency applied to the manufacturing sector and to exclude those ones related to the topics of energy production and buildings. The keywords were combined according to the following search string [*("method" OR "tool") AND ("manufactur*" OR "factory") AND ("energy assessment" OR "energy efficien*")*], where "manufactur*" included both "manufacturing" and "manufacture" and "energy efficien*" included "energy efficiency" and "energy efficient". Boolean search terms (e.g., OR, AND) were used to incorporate diverse, but reasonable keywords in one search string.

Some inclusion and exclusion criteria were defined to determine the most relevant papers from the scientific literature. Specifically, the research was limited to articles published in peer-reviewed academic journals. All other publication types (e.g., conference papers, periodicals and working papers) were excluded as they usually pass through a less rigorous peer-review process (Podsakoff et al., 2005). Articles not written in English and articles not digitally available as full texts were also excluded. No time limitation was set, and the research focused on the 'engineering' and 'energy' research disciplines.

The papers were selected based on their relevance with regard to the theme of the review. Articles that focus only on barriers and driving forces of energy management were excluded, as well as papers that address policy questions rather than management matters. The reason for this choice is that these works consider investment decisions as an analysing variable and focus on external drivers for energy efficiency (Thollander and Palm, 2012). As the focus of this research is on supporting tools and methods for industrial energy management, scientific studies involving machine tools were also excluded. These studies focus only on the energy model of the machine and analyse the relationship between the operating parameters and the production process. Methods and tools that analyse energy efficiency based on the second law of thermodynamics have been excluded. They are used to analyse only specific industrial processes (e.g., industrial ammonia synthesis, petroleum refining) or specific aspects of production process (e.g., HVAC and cooling system, solar collector systems) where energy transformation is a significant component of the system's energy consumption. Furthermore, some different reviews on energy consumption models, energy efficiency of machine tools and exergy analyses have been recently published (e.g., Zhou et al. (2016); BoroumandJazi et al. (2013)).

The modelling and analysis methods were also considered beyond the review scope. These methods differ from modelling and analysis methods because they are generic, provide short-term decision support and allow real time analysis of production processes. Indeed, the modelling and analysis methods are often developed for specific applications and for occasional use (Kádár et al., 2010) to predict the effects of intervention strategies on future scenarios and identify optimal settings through the integration of simulation and optimization activities (Debnath and Mourshed, 2018).

As a result, 64 scientific articles were selected and analysed in detail (Menghi et al., 2019). Figure 2.12 shows the time distribution of the selected articles. Most of the articles are concentrated in the last 7 years (i.e., from 2012 to 2018), highlighting the growing interest in new methods and tools for improving the energy efficiency of production processes. In particular, the attention of the scientific community has grown since the first release of the ISO 50001 standard in June 2011 (ISO, 2018). This standard strongly contributed to increasing the consciousness towards energy consumption, and stimulated scholars to look for new methods and tools, with the aims of improving energy-related performance and identifying energy savings opportunities.

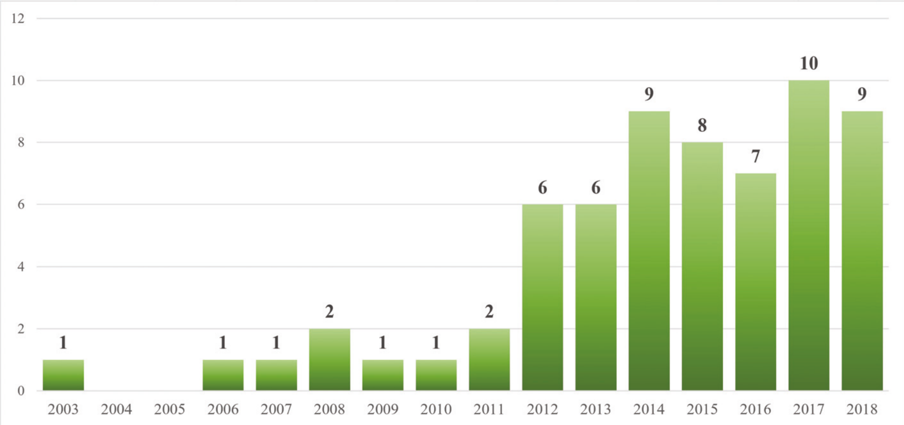


Figure 2.12: Distribution of the articles across the time period.

Starting from the analysis of the papers, energy assessment methods and tools have been defined as ***"the combination of activities, methodical procedures, standards and tools used to analyse, assess and suggest corrective actions to reduce energy consumption and increase the energy efficiency of production systems"***.

According to this definition, the single articles were classified in terms of the content and then analysed in relation to each other, allowing for classification into distinct and homogeneous groups. The methods and tools were divided into three main groups: energy analysis (E1), energy evaluation (E2), and energy-saving measures (E3), following the same principle as the ISO 50001 standard (ISO, 2018) on how to undertake an energy review (Figure 2.13).

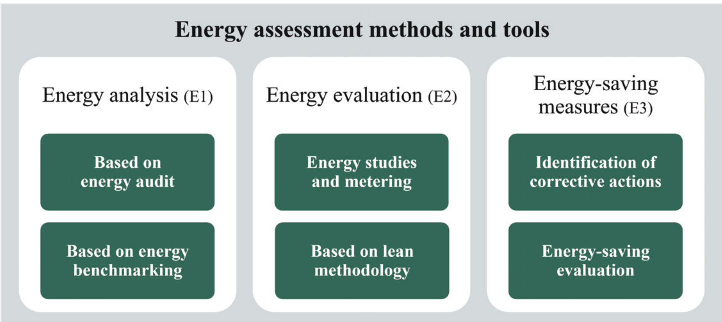


Figure 2.13: Classification of the energy assessment methods and tools.

The cataloguing was carried out based on the focus of the scientific work and on the proposed innovation. Figure 2.14 illustrates the distribution of the analysed studies by research focus. Approximately one-third of the papers (19) focused on aspects related to energy studies and metering, followed in terms of quantity by studies analysing methods based on energy audits (13) and methods based on energy benchmarking (11). A significantly smaller portion of studies focused on methods for the identification of corrective actions (8) and methods for evaluating energy savings (6).

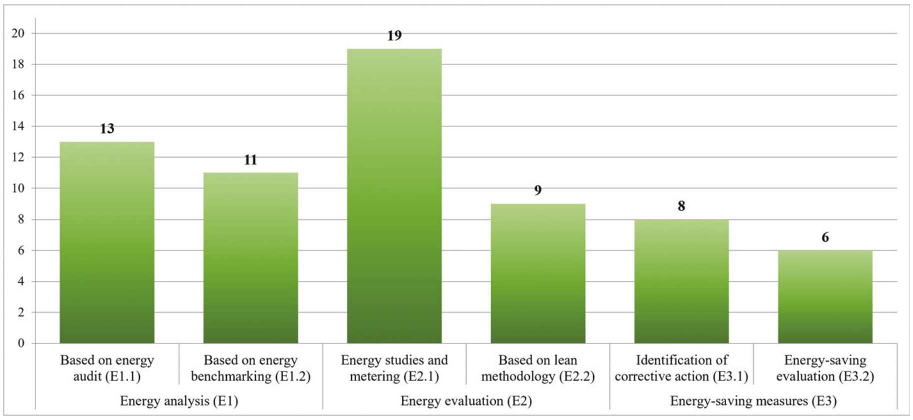


Figure 2.14: Distribution of the selected articles considering the research focus of studies.

The main characteristics and differences between the three groups of energy assessment methods and tools are described below.

2.3.1 Energy analysis methods and tools (E1)

The E1 group includes the methods and tools used to increase the transparency of the energy consumption of a production system. These tools are mainly based on an energy audit that consists of the systematic investigation and analysis of the company's energy consumers. Aggregate consumption data such as energy invoices or bills are often used as input, and national benchmarks or indicators are used to assess company efficiency. The goal is to clearly show how energy is consumed through a preliminary energy diagnosis, which is the starting point for further optimization measures and the implementation of an action plan. Two themes are prevalent in studies evaluating energy analysis methods and tools: energy consumption analysis based on energy audits (E1.1) and energy analysis through benchmarking (E1.2) (Table 2.1).

E1.1 The main purpose of methods and tools based on energy audit (E1.1) is to increase energy consumption transparency through a systematic investigation and identification of the different energy consumers within a produc-

Table 2.1: Classification of papers belonging to the Energy analysis group (E1).

Paper	Study methodology	System boundary	Group	Approach	Input			Indicator
					E	P	D	
Aguirre et al. (2011)	Conceptual approach	Plant	E1.2	DEA, linear regression models	Aggregate	✓	IAC	–
Azadeh et al. (2007)	Method + case study	Factory	E1.2	DEA, principal component analysis, numerical taxonomy	Aggregate	–	UN industrial yearbooks	–
Boharb et al. (2016)	Case study	Plant	E1.1	–	Aggregate	–	–	–
Boyd (2017)	Conceptual approach	Factory	E1.2	–	Aggregate	✓	US Census Bureau	Energy Star Epi
Boyd et al. (2008)	Tool	Factory	E1.2	–	Aggregate	✓	US Census Bureau	Energy Star Epi
Carabalı et al. (2018)	Case study	Factory	E1.1	MEFA, Sankey diagrams	Aggregate	–	–	–
Chen et al. (2012)	Case study	Factory	E1.1	Energy flow analysis	Aggregate	✓	–	–
Ghituleasa et al. (2016)	Tool	Factory	E1.2	–	Aggregate	✓	–	SEC
Gopalakrishnan et al. (2014)	Tool	Factory	E1.1	ISO 50001	Rated power	✓	–	–
Jeon et al. (2015)	Conceptual approach	Mixed	E1.2	Distribution fitting	Aggregate	–	IAC	–
Kannan and Boie (2003)	Case study	Factory	E1.1	–	Rated power	✓	–	SEC
Kluczek and Olszewski (2017)	Case study	Multi-machine	E1.1	Energy audit tools	Real-time	–	–	–
Mahamud et al. (2017)	Case study	Plant	E1.2	DEA, regression analysis	Aggregate	✓	Company	SEC
Meyers et al. (2016)	Case study	Factory	E1.2	–	Aggregate	✓	–	–
Oh and Hildreth (2014)	Method + case study	Factory	E1.2	SFA, DEA	Aggregate	✓	Company	Energy Star Epi
Richert (2017)	Method + case study	Factory	E1.1	ISO 50001	Real-time	–	–	–
Rodrıguez et al. (2011)	Case study	Plant	E1.1	MEFA	Aggregate	✓	–	–
Rogers et al. (2018)	Case study	Factory	E1.2	–	Aggregate	–	Multiple	–
Salta et al. (2009)	Case study	Factory	E1.1	–	Aggregate	✓	Multiple	SEC
Smith and Ball (2012)	Method + case study	Factory	E1.1	MEFA	Rated power	–	–	–
Taner et al. (2018)	Case study	Factory	E1.1	CUSUM	Aggregate	–	–	–
Tunc et al. (2016)	Case study	Factory l	E1.1	–	Aggregate	–	–	–
Wang et al. (2016)	Method + case study	Multi-factory	E1.2	–	Aggregate	✓	Company	Energy eff. indicators
Wojdalski et al. (2015)	Case study	Plant	E1.1	–	Rated power	✓	–	SECs

(Note: E = energy data; P = production data; D = database)

tion system. These methods allowed for the identification of the most energy-consuming processes and represented a very significant step to improve the energy efficiency of production process (Kannan and Boie, 2003; Boharb et al., 2016; Kluczek and Olszewski, 2017). They used a review of utility bills or other operating data (e.g., rated power of the equipment and their number of operating hours) and a walk-through of the facility (Kannan and Boie, 2003; Tunc et al., 2016).

Methods for the assessment of material and energy flows (MEFA) within a system have been then developed. These methods analyse the input/output relationships of processes and systems and, by their balancing and a visualization with Sankey diagrams, enable the identification of the critical areas from the energy consumption point of view (Rodríguez et al., 2011; Smith and Ball, 2012; Carabalí et al., 2018).

To assist an organization with energy analysis, (Gopalakrishnan et al., 2014) developed a tool (i.e., the ISO 50001 Analyzer software) that provides a user-friendly guide to energy audits involving all company stakeholders, without requiring a significant amount of data processing. It is based on the ISO 50001 methodology (ISO, 2018) and allows for the implementation of an energy management system. Similarly, Richert (2017) developed a methodological approach based on the ISO 50001 standard, adapted to small and medium enterprises (SMEs), for which time, personnel and budget resources are limited.

In addition, scientific literature includes methods developed starting from/for particular production sectors and/or specific geographical contexts. Taner et al. (2018) presented an energy assessment of a sugar factory. In this case, data evaluation was carried out through a statistical analysis (i.e., the CUSUM technique) and enabled the identification of specific energy efficiency indices for sugar production. Another example was proposed by (Chen et al., 2012), who analysed the energy flow of three mills in Taiwan's pulp and paper industry. Through a five-step method, the authors identified how energy is used and the amount of energy lost during the production process. Wojdalski et al. (2015) proposed a novel method of determining the direct energy consumption and energy efficiency of a confectionery plant that produces candies. Finally, Salta et al. (2009) studied the energy consumption of Greek companies in various production sectors. They developed a methodological framework for evaluating the energy consumption of different production processes and the evolution of energy utilization.

In summary, the methods and tools based on energy audits (E1.1) provide a first assessment of energy consumption through a simplified approach that requires low efforts in terms of time and knowledge (Schulze et al., 2016). They are often based on normative and standards (e.g., ISO 50001:2018) and use easy-to-find aggregate data (e.g., energy bills) (Gopalakrishnan et al., 2014; Kluczek and Olszewski, 2017). Although easily implemented, they can be used for only the high-level, strategic implementation of energy management, as they do not provide an appropriate level of detail to identify energy flows within a production plant. Attempts have been made to simplify analysis methodologies for SMEs (Tunc et al., 2016; Richert, 2017; Wojdalski et al., 2015), where energy consumption is not always considered a critical cost factor within industrial production (Schulze et al., 2016), but it is still under study.

E1.2 The E1.2 category includes all publications related to energy analyses based on national or international reference values. In this case, the evaluation of a company's energy efficiency is carried out through a comparison with benchmark values within the same production sector. Azadeh et al. (2007) presented an integrated approach based on data envelopment analysis (DEA), principal component analysis and numerical taxonomy for energy assessment. The proposed approach eliminates the need for energy data at the disaggregated operations level for considering the structural effect. It analyses and compares the performance differentials of several companies to determine the critical energy carrier and propose the optimal reductions. Aguirre et al. (2011) presented a methodology for measuring relative industrial energy efficiency between different plants within a company. The assessment is carried out by comparing national data (i.e., US Industrial Assessment Centers - IACs (DOE, 2006)) with plant data processed using a statistical approach. Specifically, through DEA and linear regression models, the parameters that influence production and the efficiency curves used to compare the plants are identified. Oh and Hildreth (2014) analysed the car manufacturing industry and described a benchmarking model based on ENERGY STAR plant energy performance indicator values. Through stochastic frontier analysis (SFA) and DEA, the study found frontier lines and measured their shifts as a proxy for structural technical energy efficiency improvement. Jeon et al. (2015) suggested a model for evaluating the energy footprints of manufacturing processes based on probabilistic techniques (i.e., SFA, probability density function, ordinary least squares regression) with the goal of benchmarking plants' energy efficiencies at the industry level. Using specific indicators and the IAC database, it compares the energy efficiency of plants with peers in the US manufacturing sector. Mahamud et al. (2017) proposed a generic methodology to characterize energy efficiency at the factory level and derive benchmarking reference points. In this case, the benchmark values are not derived from national databases but are calculated by analysing the production plant. Through an empirical approach and statistical analysis (i.e., DEA and regression analysis), this approach identifies the daily production reference value and the target to be achieved to optimize energy efficiency.

There are also scientific works that analyse specific manufacturing sectors, such as the paper and pulp industries, which were studied by Rogers et al. (2018). Their work examined the benchmarks available in the literature to identify a single reference value among all those proposed. With a similar approach, Boyd (2017) compared the statistical distributions of energy efficiency in specific manufacturing sectors. He analysed and compared the evolution over time of the benchmark distributions of energy efficiency in cement manufacturing, auto assembly and wet corn refining. Wang et al. (2016) developed a methodology for the comparative analysis of coal production energy efficiency. Their method was used to analyse eight coal mines in China and, through the definition of benchmarking indicators, their process-based energy efficiency status. Similarly, Meyers et al. (2016) investigated the energy consumption of some European SMEs in the food and beverage sector. Their method was based on a comparison of the energy analysis results and the definition of a set of benchmarking indicators, such as product-specific energy consumption, which determined the production efficiency. Finally, there are tools for analysing the energy efficiency of production plants based on comparison with national databases. Boyd et al. (2008) developed a tool that provides a "birds-eye view of sector-specific, plant-level energy use" through a correlation between the energy consumption, the level and type of various production activities and the quality of inputs and external factors. Another example is the Energy Saving and Efficiency Tool developed by Ghituleasa et al. (2016), a free tool customized for textile manufacturers. It is based on an internal database and enables the comparison of a factory's energy performance with those of similar European companies.

Resuming, energy analyses through benchmarking (E1.2) support the energy manager in comparing a plant's energy efficiency with other similar production plants (Bunse et al., 2011). The benchmarking process is useful for identifying the optimal energy efficiency value and for highlighting where improvements can be made (Aguirre et al., 2011). To support the decision-makers, the US Environmental Protection Agency has developed the Energy Star performance indicator, a statistical benchmark method for factory-level comparisons (Rogers et al., 2018). It appears to meet the requirements of industrial companies, but thus far, it is available for only eleven sectors in the US, including automotive, food, glass, pharmaceutical, paper and cement production. The main obstacle to the adoption of such methodologies is the unavailability of data or the use of inadequate or unrepresentative data, as companies are reluctant to share their data (Boyd, 2017). To overcome these limits, some attempts have been made to develop methods using their own company data instead of national statistical data and allow for the identification of optimal reference values through appropriate statistical functions (Mahamud et al., 2017). However, these methods are still in the research phase and are not ready to be implemented in real industrial contexts.

2.3.2 Energy evaluation methods and tools (E2)

The E2 group extends the energy evaluation beyond mere analysis. Indeed, the aim is to deeply investigate how energy is consumed within a production process. These methods and tools often use real time energy consumption data from IoT-based technologies (e.g., smart meters and sensors). They study and compare several production-related topics (e.g., used technology, manufacturing parameters, use patterns and production planning) and analyse their effects on energy efficiency and environmental objectives. These methods enable increased awareness and transparency of how energy is used, at the machine, process and factory levels. Energy evaluation methods and tools are divided into two main groups: the first group analyses production through new mathematical-statistical approaches and the creation of appropriate indices (E2.1), while the second group contains methods and tools developed from the lean methodology and mainly focuses on waste reduction (E2.2) (Table 2.2).

E2.1 The energy studies and metering group (E2.1) tries to overcome the lack of an effective index system and quantitative analysis methods that enable in-depth study of how energy is consumed within a production process.

Table 2.2: Classification of paper belonging to the Energy evaluation group (E2).

Paper	Study method.	System boundary	Group	Approach	Input		Indicator	
					E	P	Standard	Proposed
Benedetti et al. (2017)	Method + case study	Multi-factory	E2.1	ISO 50006, CUSUM	Real-time	✓	EnPIs	–
Cherrafi et al. (2017)	Method + case study	Factory	E2.2	Lean, Six Sigma	Aggregate	✓	Multiple	–
Cosgrove et al. (2017)	Method + case study	Factory	E2.1	ISO 50001, PDCA	Aggregate + real-time	✓	KPI, EnPI	–
Darmawan et al. (2014)	Case study	Supply chain	E2.2	VSM	Aggregate	✓	–	–
Dehning et al. (2017)	Method + case study	Multi-factory	E2.1	Multiple linear regression model	–	✓	SEC	–
Estrada et al. (2018)	Method + case study	Mixed	E2.1	–	Real-time	✓	SEC	SEC*n*, *n*-Energy Gap
Faulkner and Badurdeen (2014)	Method + case study	Plant	E2.2	VSM	Not specified	✓	Multiple	–
Finnerty et al. (2017)	Method + case study	Multi-factory	E2.1	–	Aggregate	✓	KPI	Energy management maturity model
Fysikopoulos et al. (2014)	Method + case study	Multi-machine	E2.1	–	Not specified	–	SECs	Energy efficiency
Garza-Reyes et al. (2018)	Method + case study	Factory	E2.2	PDCA, VSM	Rated power	–	–	–
Gazi et al. (2012)	Case study	Multi-factory	E2.1	–	Rated power	✓	–	–
Giacone and Mancò (2012)	Method + case study	Multi-machine	E2.1	Regression analysis	Aggregate	✓	SEC	Energy efficiency
Goschel et al. (2012)	Method + case study	Multi-machine	E2.1	–	Not specified	✓	–	Energy efficiency
Hopf and Müller (2015)	Tool	Plant	E2.1	–	Real-time	✓	–	–
Jia et al. (2017)	Method + case study	Multi-machine	E2.2	VSM, Therblig	Rated power	–	–	Energy efficiency
Lee et al. (2014)	Conceptual approach	Factory	E2.2	Six-Sigma	Aggregate	–	–	–
Li et al. (2017)	Tool	Plant	E2.1	AHP, Fuzzy evaluation	Real-time	–	–	–
May et al. (2015)	Conceptual approach	Factory	E2.1	–	Not specified	✓	KPIs	Lean Energy Indicator
Müller et al. (2014)	Conceptual approach	Mixed	E2.2	VSM	Real-time	–	–	–
Mustafaraj et al. (2015)	Case study	Multi-machine	E2.2	EVSM	Real-time	–	–	–
Perroni et al. (2018)	Conceptual approach	Factory	E2.1	–	Not specified	–	–	Energy performance
Posselt et al. (2014)	Method + case study	Factory	E2.2	EVSM	Real-time	–	–	–
Robinson et al. (2015)	Tool	Plant	E2.1	–	Real-time	✓	–	–
Savulescu and Kim (2008)	Conceptual approach	Plant	E2.1	Pinch, water analysis	Not specified	–	–	–
Vikhorev et al. (2013)	Tool	Multi-machine	E2.1	–	Real-time	✓	KPIs	–
Wang and Ji (2017)	Method + case study	Multi-machine	E2.1	Rough set, AHM grey correlation	Not specified	✓	–	Energy Efficiency Quantitative Analysis Index
Wang et al. (2013)	Method + case study	Multi-machine	E2.1	–	Real-time	✓	SECs	Process energy efficiency
Zhu et al. (2017)	Method + case study	Multi-machine	E2.1	–	Real-time	✓	–	Carbon efficiency of process chain

(Note: E = energy data; P = production data)

Göschel et al. (2012) proposed a methodology that balances inputs and outputs in terms of the energy and materials in a production line. The method considers the assembly line to be a black box, and it is based on a high level of wide-ranging and transparent data and on the mathematical description of the phenomena concerning technology and energy. A structured framework to define and measure energy efficiency was proposed by Giacone and Mancò (2012). Energy consumption is represented by a single matrix equation, which expresses the relationship between imported energies and energy drivers. The matrix is populated by specific energy consumption (SEC) indicators for each energy-consuming and energy conversion process. Benedetti et al. (2017) and Zhu et al. (2017) introduced methods for controlling the energy performance of manufacturing plants through the evaluation of specific indicators. The indexes characterize the various processing phases and identify the operations with the highest consumption.

Other studies have analysed production on additional levels and proposed integrated methods for assessing the energy efficiency of a machining workshop. Fysikopoulos et al. (2014) studied the manufacturing process in four layers, i.e., process, machine, production line and factory, each of which had multiple assessment indices that combine the effective energy indicators with SEC indicators to completely describe the energy consumption state. Wang et al. (2013) and Cosgrove et al. (2017) analysed the energy efficiency of a production process with a hierarchical approach. They proposed a novel evaluation index system with an interlinked set of key performance indicators (KPIs) to analyse the overall energy consumption level of a production system. May et al. (2015) presented a method of developing production-tailored and energy-related KPIs that enable the interpretation of cause-effect relationships. The indicators analyse several aspects of the production process, such as consumption for maintenance, consumption for non-conforming parts, and post-holiday start-up consumption, with the purpose of increasing production efficiency. Some works introduce other indicators into the evaluation of energy efficiency of a manufacturing workshop. A novel energy efficiency quantitative analysis method for multi-machine manufacturing systems was proposed by Wang and Ji (2017). They presented an energy efficiency evaluation index system that included ten indices grouped into the following categories: economic energy efficiency, production energy efficiency, machine energy efficiency and task-flow energy efficiency. Estrada et al. (2018) suggested a novel strategic decision methodology to increase energy efficiency in industrial processes. Six different specific energy consumption levels are proposed, and the differences between them are calculated in terms of production, quality, process, technological, and R& D gaps.

There are also methods developed for particular types of companies or specific manufacturing sectors. Finnerty et al. (2017) and Perroni et al. (2018) developed new methodologies to measure the energy performance of a multi-site organizations and an extended enterprise, respectively. Their methods are based on both quantitative performance evaluation, using KPIs and benchmarking, and qualitative characterization, using energy management models. Savulescu and Kim (2008) proposed a method of analysing the consumption of energy in the food industries, investigating the cross effects of energy and water systems. Gazi et al. (2012) presented a systematic approach for assessing the energy efficiency of a typical European marble quarrying and processing SME. The method analyses each individual operation to calculate the energy incorporated by each specific product. Dehning et al. (2017) introduced a statistical approach for identifying and quantifying influencing factors on the energy intensity of an automotive plant.

Some researchers focused on the development of tools for the energy assessment of a production plant. These tools help to identify the weaknesses and areas for energy efficiency improvements related to the control of production and operations. Vikhorev et al. (2013) proposed a framework for energy monitoring and management in the factory. The tool enables detailed and real time analysis of energy data and includes standards for energy data exchange, performance measurement and display of energy usage. It increases the awareness of the energy-use patterns of every part of the manufacturing plant. With a similar approach, Robinson et al. (2015) developed a tool for monitoring energy efficiency in manufacturing. Here, the tool uses specific indicators that allow the user to gain a quick overview of the current state of the system and provides numeric and graphical output about the history of the data. Additionally, Hopf and Müller (2015) presented a tool for gathering and visualizing energy usage data. The tool merges the energy data of a system with the manufacturing process data. It creates transparency on the energy-related relationships in the factory and enables the transfer of energy data, information and knowledge directly to the shop floor in a structured and clear manner. Li et al. (2017) constructed a comprehensive model for monitoring industrial energy consumption. It is based on an index system for evaluating the operational level of energy-intensive industrial equipment. Also, it uses an integrated analytic hierarchy process and a fuzzy comprehensive evaluation method to build a comprehensive evaluation model for measuring the operational level of energy-intensive industrial equipment.

In conclusion, energy evaluation methods and tools (E2.1) mainly use accurate data provided by production monitoring systems and, through appropriate indicators, allow the manager to evaluate the energy efficiency of industrial processes (May et al., 2017). Several methods and various types of indicators have been developed in recent years, but a framework that examines the production process in a holistic and multi-level way is still lacking. Due to the variety and complexity of industrial processes, the developed methods are usually specific for a given manufacturing sector and often consider only production systems by excluding auxiliary facilities (Estrada et al., 2018).

E2.2 The E2.2 category includes methods that use lean methodologies as a starting point for the evaluation of energy consumption and waste within industrial production. The lean approach provides structured methods for developing environmental management strategies to eliminate waste, simplify procedures and speed up production. The main pillars of lean philosophy are continuously and relentlessly improving value and value flow and pulling in business operations (Hines et al., 2004). Based on this approach and on several lean tools [e.g., Kaizen events, 5-why-analysis, the PDCA cycle, the A3 report, value stream mapping (VSM) and the 5S method], various methods for evaluating energy consumption have been developed. The purpose of these methods is to reduce waste and improve energy efficiency by exploiting the well-established and widely used knowledge and procedures of the lean philosophy.

Lee et al. (2014) presented a six sigma-based energy management planning procedure. The method aims to provide information and a clear understanding for establishing an equipment management plan and an energy-saving action plan. Cherrafi et al. (2017) developed a method that drives companies through a five-stage, sixteen-step process to effectively integrate and implement the green, lean and six sigma approaches. It helps enterprises in reducing consumption, increasing efficiency and minimizing environmental impacts.

There are also publications that propose methods and tools using the methodology and inner logic of VSM due to its increasing popularity, effectiveness and relative simplicity. Müller et al. (2014) developed Energy-VSM, a tool that, in addition to cycle time, correlates energy consumption with value-added and non value-added activities to quickly evaluate the energetic performance of process chains. Then, Posselt et al. (2014) and Mustafaraj et al. (2015) developed methods for analysing the extended energy value streams, considering all peripheral equipment with a low time requirement while sustaining an acceptable level of accuracy. Garza-Reyes et al. (2018) proposed a novel PDCA-based method for systematically implementing and conducting EVSM analyses. Faulkner and Badurdeen (2014) proposed a VSM-based method (Sustainable VSM) to evaluate and visualize the sustainability of the production process. It assesses the environmental (i.e., energy consumption with the usage of process water and raw materials) and social sustainability performance in manufacturing. Similarly, Darmawan et al. (2014) extended VSM to map and analyse the green productivity of a natural rubber supply chain and formulate scenarios for increasing its green productivity level. Finally, Jia et al. (2017) developed a methodology based on VSM to accurately analyse the energy efficiency of production lines. Using the Therblig symbology, the method allows a detailed evaluation of each activity and the identification of any critical points in the production process.

Summarizing, this group of methods and tools enables valorisation of energy consumption and identification of the value-adding efficiency of the process in terms of energy (Müller et al., 2014). To enable the synergies and integration among lean and sustainable production, some of the lean tools have been adapted to improve environmental performance. For instance, EVSM extended the concept of value stream, looking at it from the energy perspective, while Sus-VSM extended it from an environmental perspective (Mustafaraj et al., 2015; Faulkner and Badurdeen, 2014). The published papers highlight how these methods and tools can help organizations address sustainability challenges and comply with government environmental regulations (Garza-Reyes et al., 2018). However, certain issues, such as the inability to cope with a multi-product manufacturing system, the static nature of the method and the possibility of including more energy flows, remain unresolved.

2.3.3 Energy-saving measures methods and tools (E3)

The E3 group includes methods and tools that explore energy-saving measures. The aim is to identify and evaluate improvement opportunities to reduce energy consumption and the environmental impacts of production. They allow for the identification of appropriate energy-saving actions through the collection of relevant data and the analysis of the correlations among energy saving opportunities, risks and cost benefits. This group of methods does not include optimization methods, since they are focused on system modelling and involve discrete event simulation or the application of pure mathematical (optimization) models (Ferretti et al., 2008). Two themes are prevalent in papers analysing energy-saving measures: methods to identify corrective actions based on energy analysis (E3.1) and methods to evaluate energy-saving measures (E3.2) (Table 2.3).

Table 2.3: Classification of papers belonging to the Energy-saving measures group (E3).

Paper	Study methodology	System boundary	Group	Approach	Input			Indicator
					E	P	D	
Afkhami et al. (2015)	Case study	Plant	E3.2	ISIRI 7873, CUSUM	Aggregate	✓	–	SECs
Boyd and Zhang (2013)	Case study	Factory	E3.2	Statistical analysis	Aggregate	–	US Census Bureau	Energy Star Epi
Caldera et al. (2018)	Conceptual approach	Factory	E3.1	Natural-resource-based view theory	Aggregate	–	–	–
Fleiter et al. (2012)	Conceptual approach	Factory	E3.2	Morphological box	Aggregate	–	–	–
Hackl and Harvey (2013)	Method + case study	Multi-factory	E3.1	Pinch analysis	Aggregate	–	–	–
Hasanbeigi et al. (2010)	Case study	Plant	E3.2	Conservation Supply Curve	Aggregate	✓	LLNL	–
Kissock and Eger (2008)	Method + case study	Plant	E3.2	Multi-variable least-squares regression	Aggregate	–	–	–
Kluczek (2014)	Case study	Factory	E3.1	BAT	Aggregate	–	BREF documents	–
Lu et al. (2013)	Method + case study	Factory	E3.1	BAT world Best Practice Technology	Aggregate	–	BREF documents, IEA, LLNL	–
Müller et al. (2013)	Method + case study	Factory	E3.1	–	Aggregate	–	–	SECs
Rodrıguez et al. (2011)	Case study	Plant	E3.1	BAT	Aggregate	–	BREF documents	–
Rogers et al. (2018)	Case study	Factory	E3.1	BAT	Aggregate	–	BREF documents	–
Svensson and Paramonova (2017)	Method + case study	Factory	E3.1	–	Aggregate	–	–	–
Trianni et al. (2014)	Conceptual approach	Factory	E3.2	–	Aggregate	–	IAC Recommendation Types	–

(Note: E = energy data; P = production data; D = database)

E3.1 The E3.1 category aims to identify opportunities for reducing energy consumption and the environmental impact of production. Rodríguez et al. (2011), Lu et al. (2013), Kluczek (2014) and Rogers et al. (2018) applied the best available techniques (BAT) approach. These approaches aim to identify corrective actions through the selection of the best technology to improve environmental sustainability and energy efficiency. These methods, applied to different production sectors, are based on the Integrated Pollution Prevention and

Control Directive (2008/1/EC) by the European Commission (European Commission, 2008) and they enable a significant reduction in the required energy. Then, there are methods that systematically identify energy efficiency measures based on qualitative information about a process. Müller et al. (2013) developed the "Energy Efficiency Model", an approach that decomposes the problem and describes the underlying causes and parameters for energy consumption, to define fundamental energy efficiency approaches. Hackl and Harvey (2013) introduced a framework methodology for investigating options to increase energy efficiency in industrial clusters. Svensson and Paramonova (2017) presented a method for identifying possible energy savings in industrial plants based on theoretical research. It involves all stakeholders and analyses overall energy efficiency, rather than narrowly focusing on the simple installation of energy-efficient technologies. Caldera et al. (2018) analysed the key characteristics of sustainable measures for SMEs by evaluating the experiences of experts. The proposed method evaluates efficiency practices by establishing nine characteristics under three themes: environmental stewardship, process excellence, and a sustainability-oriented culture.

E3.2 The E3.2 category includes publications that propose methods and tools that characterize energy efficiency measures. Kissock and Eger (2008) proposed a general method for measuring industrial energy savings. The method uses multivariable piecewise regression models to characterize baseline energy use, and it disaggregates savings into weather-dependent, production-dependent and independent components. Fleiter et al. (2012a) presented a method of classifying energy efficiency measures based on the available scientific literature. It analyses twelve different characteristics of energy efficiency measures that are independent of the type and size of the company and focuses on the relative advantage, technical context and information context. The classification scheme is designed to improve the understanding of their adoption by industrial enterprises and to assist the decision-maker in selecting and implementing the best energy-saving action. Trianni et al. (2014) proposed an innovative and comprehensive framework for characterizing energy-saving actions using 17 attributes grouped into six categories: economic, energy, environmental, production-related, implementation-related and possible interaction with other systems.

There are also papers that focus on specific production sectors, such as cement production since this industry is considered to be one of the most energy-intensive industries. Hasanbeigi et al. (2010) proposed a 5-step methodology for analysing energy efficiency improvement. The method summarizes both engineering and economic viewpoints, and it is based on the bottom-up conservation supply curve, the cumulative cost-effective and the technical electricity and fuel savings models. Boyd and Zhang (2013) proposed an approach based on the assessment of the energy performance indicator defined by the US Environmental Protection Agency. Another approach for evaluating the potential of energy efficiency measures was suggested by Afkhami et al. (2015). They proposed a statistical approach based on the cumulative sum of differences technique (CUSUM) to evaluate savings actions at the time of deployment.

In conclusion, the energy-saving measures (**E3.1** and **E3.2**) support the energy manager in the last step of the manufacturing system evaluation process. They enable the assessment and identification of the best intervention approach to reduce the energy and emissions footprints of the production process (Kissock and Eger, 2008). Only a few studies have been published in this group, and some focus on only a specific industrial sector, such as cement production (Hasanbeigi et al., 2010; Boyd and Zhang, 2013; Afkhami et al., 2015). There is no comprehensive theoretical methodology to support decision-makers in the implementation of energy efficiency measures in production processes. To overcome these barriers, methodologies for implementing BAT have been developed (Rodríguez et al., 2011; Lu et al., 2013; Kluczek, 2014), but they are still specific to an industrial sector and not applicable in every production context.

2.3.4 Assessment of methods and tools

The previous sections present the description and the classification of methods and tools to increase energy efficiency in factories. In this section, a critical assessment of the main identified methods and tools is made in order to highlight the current limits and challenges of research.

The selected criteria for the assessment consider both technical issues in the context of energy management in manufacturing [e.g., implementation strategy (Schulze et al., 2016), analysis objectives (Cherrafi et al., 2016), best-practices (Subramanya, 2011)] and barriers to the adoption of energy-efficiency measures in different contexts [e.g., SMEs (Fleiter et al., 2012b), high energy-consuming industries (Li and Tao, 2017)].

The main criteria used for the evaluation are:

- Input data (*Data*): data collection is a very significant issue in the application of a method as it influences the effort in terms of time and resources. Specific competences might be required to gather the required data (e.g., expert estimation on expected savings or calculation of machine tool yields). The level of input data is considered low when a huge amount of data are necessary. The medium level requires a huge amount of available data while in the high level, few and available data are required to operate a system.

- Completeness of flows (*Flows*): the energy assessment method should consider all the energy flows of the system and not be restricted to a single energy carrier. This criterion is considered low for the assessment methods that consider only one energy flow, medium for more than one energy flow and high if the assessment of energy flows is conducted correlating production data.

- Completeness of systems (*Systems*): the method should consider the whole factory in order to maximize the saving effects of energy efficiency strategies. This means that production processes, logistics, process technology and technical building systems (TBS) should be considered in the analysis. A low assessment is given when the method evaluates only the production process, while a medium assessment requires the analysis of the factory excluding the TBS. A high evaluation is reached when the energy efficiency evaluation is carried out on the whole factory system.

- Type of assessments (*Assessment*): the type of assessment affects the quality of the outcomes. Analyses performed on long periods and not contextualized do not allow to identify intervention strategies, while assessments performed on real time provide detailed and accurate data. A low valuation refers to off-line analyses that are carried out on certain periods and later than when they occur. Real time analyses allow timely evaluations of the energy efficiency of the production process and refer to a medium evaluation. When the method allows both off-line and real time analysis, the evaluation is high.

- KPI: the implementation of specific indicators will enable the method to improve the monitoring and auditing of energy efficiency. The use of absolute and aggregate values only provides an overview of the production process, while the employment of indicators gives useful support to decision-makers. In detail, the introduction of specific KPIs allows to: *(a)* identify the company's specific energy drivers, *(b)* recognize cause-effect relationship and prepare actions for improvement measures and *(c)* communicate with all other stakeholders (May et al., 2015). The assessment is low if the method does not use KPI, medium if it uses only energy consumption indicators and high if the indicators are related to multiple topics.

- Improvements: Another important parameter for the evaluation of methods is the support in the design of an improvement programme. As established by the ISO 50001 standard (ISO, 2018), after the evaluation of energy efficiency it is essential to plan the corrective actions to improve the performance of the production system. Methods that do not support the energy manager in developing an improvement program are rated low while a medium evaluation refers to methods that only highlight the critical problems of the production process. A high valuation can be achieved when the method suggests corrective measures to the identified inefficiencies.

- Usability: the methods are assessed regarding the usability and the clarity of their description. A usable method is characterized by a clear and detailed description of each step, which allows users with professional knowledge to apply the method. In detail, a method is considered with low usability if significant investment in training and learning time are necessary. Medium usability if minimal training for experts are required while high usability if the minimal training for all stakeholders are needed.

The results of the assessment highlight that none of the analysed methods and tools completely fulfil the identified criteria and meet the needs of industrial companies in the area of energy management in production (Table 2.4).

In detail, most of them focus on quantitative analyses of consumptions (often only energy) with the aim to increase (energy) awareness rather than on the efficiency analysis. The attention is mainly placed upon the evaluation and visualization of energy consumption information, while research on how to examine and use real time energy data to provide chances for enhancing efficiency is insufficient. A framework that examines the production process in a holistic and multi-resource way is still lacking. The methods are usually specific for a given manufacturing sector and often consider only production systems.

Moreover, it emerged that existing methods and tools do not provide appropriate indices and/or KPIs to analyse the energy use profiles of machines and processes. The limited use of specific KPIs does not enable the identification of the less efficient operations and/or departments and the practical solutions to improve the manufacturing process performance. Additionally, only few KPIs are suitable at the process and plant levels and standardized indicators are missing. Further shortcomings concern the complete representation of the factory system (i.e., the flows completeness and the TBS evaluation) and the real time analysis of the production process.

Table 2.4: Evaluation of selected methods and tools based on the identified criteria

Method & Tool	Data	Flows	Systems	Assessments	KPI	Improvements	Usability
Aguirre et al. (2011)	○	–	–	–	○	–	○
Azadeh et al. (2007)	○	–	–	–	○	–	–
Benedetti et al. (2017)	–	•	•	–	•	–	○
Boyd (2017)	•	–	•	–	○	–	○
Boyd et al. (2008)	•	–	•	–	○	–	•
Caldera et al. (2018)	–	○	○	–	–	–	–
Cosgrove et al. (2017)	○	–	–	○	○	○	○
Dehning et al. (2017)	○	–	○	–	•	–	○
Estrada et al. (2018)	○	–	–	○	•	–	○
Faulkner and Badurdeen (2014)	•	○	–	–	–	○	•
Finnerty et al. (2017)	○	–	•	○	–	–	–
Fleiter et al. (2012a)	–	–	–	–	–	•	–
Fysikopoulos et al. (2014)	○	–	○	–	–	–	–
Garza-Reyes et al. (2018)	○	○	○	–	–	–	○
Ghituleasa et al. (2016)	•	–	•	–	○	–	•
Giacone and Mancò (2012)	–	○	•	○	–	○	○
Gopalakrishnan et al. (2014)	○	–	○	–	–	–	•
Göschel et al. (2012)	○	○	○	○	–	○	○
Hackl and Harvey (2013)	–	○	○	○	–	○	–
Hopf and Müller (2015)	•	–	•	•	○	–	○
Jeon et al. (2015)	○	–	–	○	○	○	–
Jia et al. (2017)	○	○	–	–	–	○	○
Kissock and Eger (2008)	–	○	○	–	–	○	–
Lee et al. (2014)	○	○	○	–	–	–	○
Li et al. (2017)	–	○	•	–	○	○	–
Lu et al. (2013)	○	–	○	–	○	○	○
May et al. (2015)	○	–	–	–	•	○	○
Müller et al. (2013)	–	–	○	–	○	•	○
Oh and Hildreth (2014)	○	–	–	–	•	○	–
Perroni et al. (2018)	○	○	○	–	•	○	–
Posselt et al. (2014)	○	○	○	–	–	○	○
Richert (2017)	○	–	–	–	–	○	–
Robinson et al. (2015)	○	–	–	•	–	○	–
Savulescu and Kim (2008)	–	○	•	–	–	–	–
Smith and Ball (2012)	–	○	○	–	○	○	○
Svensson and Paramonova (2017)	○	–	○	–	○	–	○
Trianni et al. (2014)	–	–	–	–	–	•	–
Vikhorev et al. (2013)	○	–	○	○	○	○	–
Wang and Ji (2017)	•	–	•	•	•	○	–
Wang et al. (2013)	–	–	–	•	○	○	–
Wang et al. (2016)	–	–	○	–	○	○	–
Zhu et al. (2017)	–	–	○	–	•	○	○

(Note: – : low; ○ : medium; • : high)

Lastly, as regards the tools, it emerged that only few software tools are developed to to support the energy manager in managing and improving the overall energy performance of an industrial process. They belong to the energy analysis (E1) and energy evaluation (E2) groups, while there are no tools for the identification and evaluation of improvement opportunities (E3). The tools belonging to E1 group provide user-friendly guide to energy audits: they allow to simplify procedures and data collection (Gopalakrishnan et al., 2014) and analyse the energy efficiency of production plants based on comparison with national databases (Boyd et al., 2008; Ghituleasa et al., 2016). However, such software tools can only be used for certain industrial sectors. The tools belonging to E2 group allow to identify weaknesses and inefficiencies of the production process (Vikhorev et al., 2013). They make it possible to increase awareness of the energy consumption patterns of every part of the manufacturing plant. In addition, they use specific indicators that allow the use to have a process control dashboard and provide graphical outputs on the system current state (Robinson et al., 2015; Hopf and Müller, 2015; Li et al., 2017). However, software tools are often developed and implemented for specific production systems and the validation in heterogeneous production sectors is scarce.

Chapter 3

Method to assess the energy efficiency of manufacturing systems

To address the limitations identified in the research background chapter, a comprehensive method has been developed to visualize and assess manufacturing process flows and extract meaningful insights from data to improve energy efficiency. The requirements for defining the method to evaluate the energy efficiency of a production system are described in the following paragraphs.

The complexity of the implementation represents a barrier for the applicability of methods. The proposed method seeks to allocate, represent and analyse energy efficiency in a simple way by exploiting the established and widely used knowledge and procedures of the lean philosophy. The aim is to develop a transparent, usable and comprehensible method that allows the knowledge exchange between all operators. This is especially important since the long-term improvement of energy efficiency is based on knowledge in a company instead of external and temporary specialist consultancies.Therefore, a systematic step-by-step procedure has been developed to guide a user through the application of the method.

The assessment of energy efficiency needs to address the entire factory system. However, most of the existing approaches focus only on production processes. Using a hierarchical approach to the problem, the method seeks to analyse the production system with different zoom levels. This approach allows performing a complete assessment of the factory systems both off-line and real time.

The method correlates data related to energy, resources, production and manufacturing activities to calculate specific, understandable, and effective KPIs, which easily allow identifying inefficiencies from an environmental and economic perspective. It tries to overcome the lack of appropriate indices and/or KPIs to analyse the energy use profiles of machines and processes. In addition, the analysis results will be displayed through an innovative, simple and clear dashboard to communicate insights to different stakeholders.

Many existing methods and tools support the analysis and evaluation in order to create transparency on energy consumption while neglecting the suggestion of corrective actions. The proposed method tries instead to provide solution approaches, i.e., concrete measures to increase energy efficiency. It supports the energy manager in the definition of a concrete and feasible action plan to effectively address inefficiencies.

As a result of these requirements, a method to assess the energy efficiency of a production system has been developed. The method aims to evaluate energies hotspots at different levels of detail, providing qualitative and quantitative feedbacks to improve the factory energy efficiency. As shown in Figure 3.1, the method consists of five steps.

It allows an organization to follow a systematic approach in achieving continual improvement of energy efficiency, including energy use and consumption. It is based on an iterative process as proposed in ISO 50001 standard (ISO, 2018). According to the PDCA methodology approach, the method allows to identify and analyse the production process (through data collection and data analysis), to support the design of corrective actions and finally to implement and verify the results obtained. According to the continuous improvement approach, the method should be iterated continuously to identify current and future scenario inefficiencies.

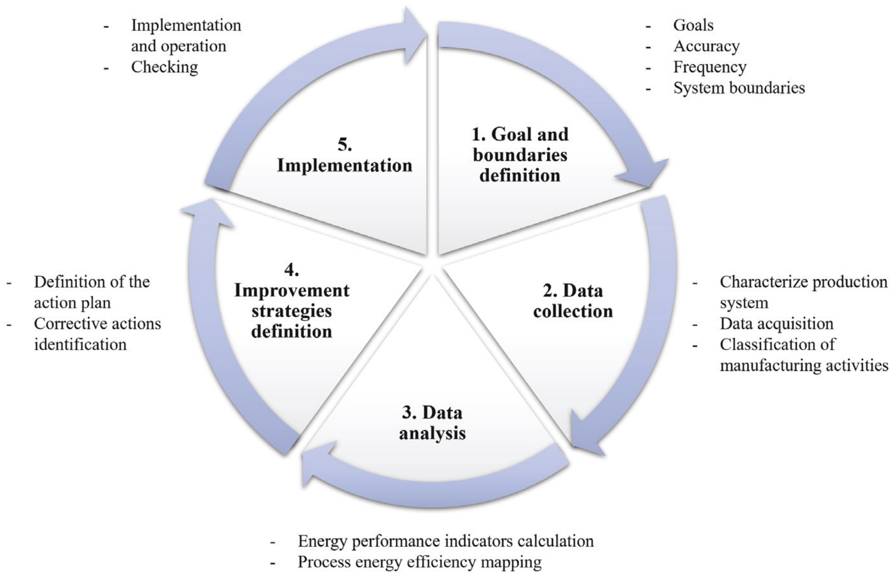


Figure 3.1: Energy efficiency assessment method concept diagram

3.1 Goal and boundaries definition

The first step of the method is the definition of the goal and the boundaries of the analysis. In detail, a consistent analysis requires the definition and sharing of the following aspects: goals, accuracy, frequency and system boundaries.

Goals Setting clear and measurable goals is critical for understanding intended results, developing effective strategies, and reaping financial gains. Well-stated goals guide the analysis process and are the basis for tracking and measuring progress. In addition, communicating and posting goals can motivate staff to support energy management efforts throughout the organization. The main objective should be clear and measurable, with target dates, for the entire organization and facilities. Company drivers and stakeholders' expectations should guide the definition of the analysis goal. For example, the goal could be the simulation of machine operation from an energetic point of view or the awareness of company global consumptions. Possible scenarios, choices or hypotheses should be also described in this phase.

Accuracy The accuracy of analysis results strictly depends on the information granularity. The level of detail of the information is specified according to the project objective. On the one hand, the method can be used to conceive general principles to improve energy efficiency of a factory in a specific industry sector. On the other hand, a high level of detail could be applied in cases where detailed insights into the technical parameters of a system are analysed. A high level of detail requires the combination of direct measurements, asset characteristics and production data, while a lower level of detail could be limited to a preliminary allocation of consumptions on the basis of utility bills.

Frequency Considering the frequency parameter, a static, dynamic or hybrid analysis could be performed. A static analysis is carried out once to have a clear picture of the state of the art (e.g., in occasion of an audit to pursue an energetic certification) and implies off-line interventions. A dynamic analysis is based on the continuous monitoring of assets, requires real time data, and enables both on-line and off-line actions. A hybrid analysis can be viewed as a combination of static and dynamic analyses. It is based on the periodic manual update of the initial analysis to verify the achievement of established objectives.

System boundaries The system boundaries demarcate the limits of the analysis. It could focus on a single machine, on production areas, on the whole shop floor, etc. It could involve all energy flows or only a subset of them. It could refer to different time slots, from a single cycle time to the entire annual production. It could consider one or more products or product families (i.e., groups of goods that undergo similar production processes). According to the hierarchical model, different levels of detail can be adopted. The system boundaries definition is strictly related to the main goal of the analysis and additional available data coming from previous studies (e.g., Pareto analysis, cost deployment).

The choices made at this stage enable different analysis scenarios, as shown in Figure 3.2. The user should accurately choose the parameters of the analysis as they will influence the following assessment activities. They must be selected according to the expected results and the required effort in terms of time and/or knowledge. They have to be clear and well defined, and shared among all stakeholders. The trade-off between results and resources will define the analysis scenario and the next phase of data collection.

	Low — Level of detail →	**High**
Frequency	Static analysis	**Dynamic analysis**
Information granularity	Utility bills analysis	**Real-time measurements**
Asset boundaries	Plant	**Hierarchical model** *(from plant to single machine)*
Production boundaries	Product cycle time	**Overall annual production**
Flows boundaries	Electrical energy	**More energy flows**
Efficacy	Offline interventions	**Online and offline interventions**

Figure 3.2: Scenarios for energy efficiency analysis

3.2 Data collection

After identifying the scenario and the boundaries of the analysis, the next step is the data collection. It is a central phase of the method since its results will influence the subsequent data analysis and the identification of corrective actions. The lack of values or incorrect data can compromise the outcomes of the energy efficiency analysis of the production process. For this reason, it is important that the data are easy to collect, that is, values that can be obtained easily and quickly, and simple to analyse, should be used.

It begins with the qualitative characterization of the production system. The aim is to analyze all processes within the area of investigation, identify energy flows, equipment and production flows. Then, the acquisition of energy consumption data and all other parameters that influence efficiency (e.g., cycle times, working hours, maintenance, etc.) is carried out. The last activity concerns the classification of activities according to the lean methodology.

3.2.1 Characterize production system

The characterization of the production system is based on a deep investigation of the processes through a physical observation of the plant and the production lines. These actions can affect both the technological and the organizational level. The aim is to characterize the functioning of the production process by identifying energy and production flows. For this reason the plant manager, the energy manager, the production manager and the technical manager are involved. This process can point out elements that at first glance may not be important or even they might escape the attention of the observer. In this way, the know-how of all stakeholders is shared and the main weaknesses and strengths of the process are identified in advance.

In detail, a comprehensive overview of the plant is carried out in order to fully understand how energies are used, to allocate consumption correctly and to interpret the results effectively. It means to analyse the physical configuration of the manufacturing plant, which affects the efficiency of subsequent operations, and all production flows (materials, resources, information, etc.). Consolidated techniques such as IDEF0 (i.e., Integration DEFinition), UML (i.e., Unified Modeling Language), etc. can support the identification of all production steps and the related input, output, constraints and resources. A deeper level of detail is achievable whether the process is analysed on site and data are acquired through plant walks (i.e., Gemba walk).

The process is schematized through block diagrams, which represent the productive activities with their input, output and mechanisms. Each activity is hierarchically decomposed to a greater level of detail. The use of a mapping tool of the process (e.g., IDEF0), followed by detailed quantitative analysis, is useful to understand the interactions within the system. Starting from the context diagram it is possible to divide the process into actions or activities. Each activity is then divided into sub-actions up to the achievement of the desired level of detail. Each activity must include: *a)* input: what is required to perform the particular activity; *b)* output: the product of the activity: *c)* controls: all the constraints and the procedures that the activity must follow; and *d)* mechanisms: tools which are necessary to carry out the activity, including energy carriers and labour.

The output is a first scheme of the production system representing the following items:

- Layout, which is the physical arrangement of machines, shops, cells, etc. within the plant;
- Processes, which refer to a single operation or a sequence of operations performed on a product by machines, operators or both;
- Energies, which are required to perform the operations, such as electrical energy, thermal energy, compressed air, etc.;
- Product path, which is the sequence of processes followed by a single product or product family.

3.2.2 Data acquisition

It mainly consists in accurately and methodically collect data that are then used for the assessment phase. It is crucial to follow a defined structure in data collection in order to avoid inadequate situations in further steps. The simplicity of the collection and analysis is not universal. It depends on the business structure and on the level of monitoring that is carried out. The data collection and classification concerns information on *(i)* energies, *(ii)* activities and *(iii)* processes.

The first item refers to energy flows. If specific sensors are available, these data can be automatically collected. If not, bills and meters are the main information sources. In both cases, the processes that contribute to each consumption need to be specified. In the case of temporary monitoring, it should be considered that the energy consumption of production related technical equipment is typically not constant over time but dynamic depending on the production process and the actual state of the machine. Machines consist of several energy consuming components that generate a specific energy load profile when producing. This applies to electricity, but is also true for other forms of energy or media like compressed air, process heat, gas or coolants. In terms of sampling time, high resolution sensors provide high informational degrees in dynamic flow charts allowing detailed process analysis but result in high volumes of data to process and store. In contrast to that, low resolutions in time allow only rudimentary meter readings but ensure low data volume and significantly lower costs per metering point. The accuracy and therefore the information content sharply decreases with higher sampling rates.

The second item includes all asset characteristics such as name, power, operating time, etc. These data can be gathered by consulting the plant manager, machine plates and manuals, plant design documents, etc. The rated power is a standard value that is supplied by the manufacturer to enable the design of the auxiliary equipment (e.g., compressor, mains connections). This is a maximum value and often tends to be significantly higher than the actual energy demand of that specific operation. However, it can be used as a reference value or to estimate energy consumption. The operating time is a value relative to the machine and can be obtained from data of manufacturing execution system or can be calculated from monthly production data. Some of these data can vary according to the product family, therefore, different values must be collected for each station/process.

Finally, the third item refers to the production flow. For each product, the logic interdependencies of activities, processes and flows within the factory have to be formalized according to the level of established detail. In this way, the production flow can be associated with the energy flow for a specified product.

3.2.3 Classification of manufacturing activities

In parallel with the definition of the flow, manufacturing activities are classified according to the principles of the lean philosophy (Hamel, 2010). This methodology makes it possible to differentiate the activities into:

- Value-added (VA) activities are operations for which the customer is willing to pay. They include all operations that change the state of a component/semi-finished part and are necessary to realize the product. These activities refer to only compliant products;

- Non value-added (NVA) activities include operations that are necessary but do not transform the product toward completion. The customer does not care for them;

- Waste (W) activities include operations that do not transform the item toward completion and are unnecessary. They usually generate extra costs: the customer is not willing to pay for them.

For example, considering a plate painting operation, only the application of the paint on the plate surface is VA. The movement of the plate to favor the painting process is NVA, while the excess of paint or compressed air to apply the paint on the plate can be classified as W.

This classification plays a key role in the evaluation of process performance with respect to the optimal consumption of energy. Specifically, it allows to understand the energy value flow and focus the improvement strategies toward the minimization of resources consumed by W and NVA activities.

Based on the work of Ohno (1988), a general classification of activities is proposed in Table 3.1. Some activities could be classified both as NVA and W, depending on the specific case. For example, considering the activity "Movement of materials or products", it should be classified as NVA if it refers to the space to be covered from one station to the next, or as W if it includes extra movements from those ones strictly needed (e.g., bad layout, inefficient production scheduling).

If the analysis refers to more than one cycle time, other data related to production need to be collected, such as pieces produced, non-compliant pieces, maintenance interventions, etc. In case of aggregate data (i.e., referred to more than one product or product family), also proper allocation criteria must be selected (e.g., quantity, turnover, etc.).

Table 3.1: Classification of manufacturing activities according to lean principles

ACTIVITY *(energy consumption for...)*	**VA**	**NVA**	**W**
Processing of compliant products	×		
More (or faster) production than required (overproduction)			×
Inventory of products, materials, energy, etc.		×	×
Production of non-compliant products (defects)			×
Performing processes that are not required or with inappropriate techniques, oversize equipment, etc.			×
Machinery setup		×	
Movement of materials or products		×	×
Movements of man or machine		×	×
Transport of resources		×	×
Corrective maintenance			×
Preventive or predictive maintenance		×	
Waiting, that is no operation is occurring		×	×

3.3 Data analysis

In this step, the collected data are analysed to highlight how each process contributes to the consumption of each energy, highlighting the VA, NVA and W percentage. It is based on the determination of appropriate indicators and data visualization.

The indicators serve as a measure to decide whether a system is working as it is designed for and helps define progress toward a pre-set target. This enables better monitoring and control of energy consumption which is of utmost important both for current and future enterprises to improve energy efficiency in production. In fact, absolute values and aggregated measures (e.g., energy consumption per year or similar measures) provide only an overview on the status quo, it fails to provide decision-making support, transparency and clear identification of action items. Decision-makers need energy efficiency indicators in order to *(i)* identify energy drivers in their production system,*(ii)* make the energy behaviour profile of the production system transparent, *(iii)* recognize cause-effect-relationships, *(iv)* prepare actions for improvement measures, and *(v)* communicate status quo adequately with other inter- and intra-functional areas. Therefore, suitable indicators according to lean approach are developed to support companies in controlling and managing the energy efficiency of the process.

The indicators are visualized through a map. The proposed map is visual, clear and linear for a simplified interpretation. It is based on a proper data management and a user-friendly structure that allows easily detecting possible inefficiencies. It can be defined as the layout of plant energies consumptions. It combines and displays energy data and information on production processes in a structured and clear manner. It focuses on a simple way to provide energy information in a factory, especially for a wide range of personnel and for direct use in the production floor.

3.3.1 Energy performance indicators calculation

In this section, indicators are defined to analyse the energy efficiency of the production process, to allow the interpretation of cause-effect relationships and therefore support companies in the operative decision-making process. The indicators consist of energy consumption data and production data gathered from shop floor in discrete or continuous time, and highlights efficiency levels for different energy-consuming productive activities. The equations for calculating the indicators are described below. According to system boundaries, they are calculated for single machinery, single process, and the overall plant.

First of all, the amount of energy consumed by the different activities is determined. Based on the classification of the section 3.2.3, the energy is divided into:

E_{VAi} is the amount of energy i consumed by VA activities j. It means the minimum amount of energy i theoretically necessary to transform a material or a semi-finished product into a product (e.g., heat necessary to quench a steel component). However, theoretical consumption is influenced by multiple factors (e.g., set-up, obsolescence, product heterogeneity) and its calculation requires an excessive effort. Therefore, in real industrial contexts and when a continuous monitoring system is not available, E_{VAi} is calculated as sum of hourly consumptions per piece of VA activities (e_{VAij}) multiplied by their duration. Therefore, a between theoretical and measured/estimated values, which refers to machinery inefficiency (energies waste), should be considered. The consumption should be as close as possible to the theoretical consumption, which represents the minimum amount of energy required for the considered processing.

$$E_{\mathrm{VA}i} = \sum_j e_{\mathrm{VA}ij} \times t_{\mathrm{VA}ij} - \Delta \tag{3.1}$$

E_{NVAi} is the amount of energy i consumed by NVA activities j. It means the amount of auxiliary energies required by the process, which does not add value to the material or semi-finished product, but is necessary to run the process in a correct way (e.g., energy required to position the component). It is obtained as sum of hourly consumptions per piece of NVA activities (e_{NVAij}) multiplied by their duration:

$$E_{\mathrm{NVA}i} = \sum_j e_{\mathrm{NVA}ij} \times t_{\mathrm{NVA}ij} - \Delta \tag{3.2}$$

E_{Wi} is the amount of energy i consumed by W activities j. It means the amount of energies lost because of wrong use of machineries, failures, or inappropriate use of equipment (e.g., use of oversized electric motors). It is obtained as sum of hourly consumptions per piece of W activities (e_{Wij}) multiplied by their duration:

$$E_{\mathrm{W}i} = \sum_j e_{\mathrm{W}ij} \times t_{\mathrm{W}ij} - \Delta \tag{3.3}$$

The hourly consumptions per piece have to be estimated or measured according to the product families and machines setting. A preliminary check of the flows mapping goodness can be executed by comparing the sum of E_{VAi}, E_{NVAi} and E_{Wi} with the total energies consumption measured. If they differ, some sources of waste are missing. If the extent of such difference is not negligible an in-depth analysis is required.

After calculating the energy consumption, the yields of the different activities are calculated.

$\eta_{\mathrm{VA}i}$ is the yield related to the energy i consumed by VA activities with respect to the total amount of consumed energy. Ideally, it should be 100%.

$$\eta_{\mathrm{VA}i} = \frac{E_{\mathrm{VA}i}}{(E_{\mathrm{VA}i} + E_{\mathrm{NVA}i} + E_{\mathrm{W}i})} \tag{3.4}$$

$\eta_{\mathrm{NVA}i}$ is the yield related to the energy i consumed by NVA activities with respect to the total amount of consumed energy. This value should be minimized.

$$\eta_{\mathrm{NVA}i} = \frac{E_{\mathrm{NVA}i}}{(E_{\mathrm{VA}i} + E_{\mathrm{NVA}i} + E_{\mathrm{W}i})} \tag{3.5}$$

$\eta_{\mathrm{W}i}$ is the yield related to the energy i consumed by W activities with respect to the total amount of consumed energy. Ideally, it should be 0%.

$$\eta_{\mathrm{W}i} = \frac{E_{\mathrm{W}i}}{(E_{\mathrm{VA}i} + E_{\mathrm{NVA}i} + E_{\mathrm{W}i})} \tag{3.6}$$

Finally, two indicators are calculated: Cost Index, which quantifying the energies consumptions from an economic point of view, and Muda Index, which highlights the consumptions not related to VA activities.

Cost Index (CI) allows identifying which process is responsible of the highest cost related to energies consumptions. It is obtained as sum of unitary cost of the energy (c_i) multiplied by the relative total amount of energy consumed:

$$CI = \sum_i c_i \times (E_{\mathrm{VA}i} + E_{\mathrm{NVA}i} + E_{\mathrm{W}i}) \tag{3.7}$$

Muda Index (MI) allows quantifying the cost of energy not related to VA activities. The basic idea of this index is to provide a clear representation of flows criticalities, other than a clear representation of energy flows. The more the MI value is higher, the more corrective actions are needed for the considered operation/process. The index has been developed in collaboration with industry experts to make it as useful and easy to interpret as possible. It is calculated according to the following equation:

$$MI = \sum_i c_i \times (E_{\mathrm{NVA}i} + 2 \times E_{\mathrm{W}i}) \tag{3.8}$$

Regarding the energy consumed by W activities, they are multiplied by a coefficient major than one in order to particularly focus the indicator on wasted energies. Indeed, according to lean philosophy principles, which constitute the basis of the proposed method, the analyses and definition of corrective actions should be mainly focused on the identification and minimization of W activities, while NVA activities should have less priority. This weighting choice has been defined empirically by mapping and deeply analysing different common processes of manufacturing industries (e.g., milling of metal parts, casting, injection moulding, etc.). In particular, the value of the multiplication factor for wasted energies has been defined after testing three different values (i.e., 1, 1,5 and 2) in several experimental case studies of different companies (Papetti et al., 2019). Results shows that by using a multiplication factor of 1 or 1,5 it is difficult to identify the most impactful energy. By using a multiplication factor of 2, the differences among the MI_i calculated for the different energies are amplified and the most critical energy is better highlighted.

3.3.2 Process energy efficiency mapping

After collecting all the necessary data, the process energy efficiency is mapped. The first step of this process is the division of the shop floor layout into areas or processes, which will remain the same for all energy carriers and analysed products. In this manner, the reading of the map is simple, as it allows to quickly identify the location of the processes and the use of energy vectors for each area. Subsequently, the processes are interconnected through links to highlight the manufacturing flow of each analysed product. This creates a natural connection between the maps of the different energy sources and the production flow.

After determining the map structure, the "*Process box*" is defined (Figure 3.3). It is the core of the map and describes each considered production process according to its impact on energies consumption. It consists of three sections:

- The upper part of the box contains the ID of the process. It is characterised by a name and an identification number. In detail, the number is determined in hierarchical order to illustrate the interrelationships in the factory system or also in a manufacturing system. The regarded object is allocated in a defined factory level by the hierarchical order (e.g., workstation, section or building). Based on this, the factory can be assembled with these subsystems from bottom to top.

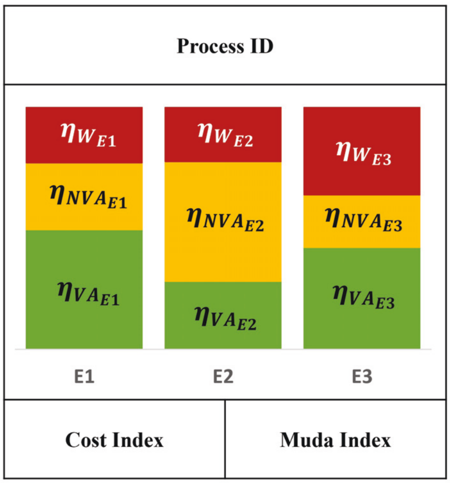


Figure 3.3: Example of Process Box

- In the central part, the allocation of energies consumption, by means of yields and coloured bars, is represented.
- In the lower part the values of the Cost Index, which allows quantifying the energies consumptions from an economic point of view, and of the Muda Index, which highlights the consumptions not related to VA activities, are reported.

This structure avoids “infobesity”, since the box only embeds the essential information needed by decision-makers to understand: *(i)* where the criticalities in terms of energies consumption are located, and *(ii)* how much margin of improvement exists for each process.

The production line is the result of sequential processes, therefore, in the map, the process boxes are connected by the paths of the different product families. In order to make the comprehension intuitive, the position of process boxes should respect the real plant layout (Figure 3.4).

The map can refer to all products and flows or single product and energy. In the first case, each box includes the total consumption generated by the specific process and the related cost. In the second case, only the consumptions of the selected energies generated by the production of the selected product are shown in the box and the cost index is recalculated accordingly.

As shown in Figure 3.5, the method exploits the hierarchical data management technique, which allows exploding in size a process box going down in the hierarchy. In order to ensure a proper hierarchy modelling, it is worth to specify that the sum of consumptions of all lower-level processes has to be equal to the energies’ consumption of the related higher-level process.

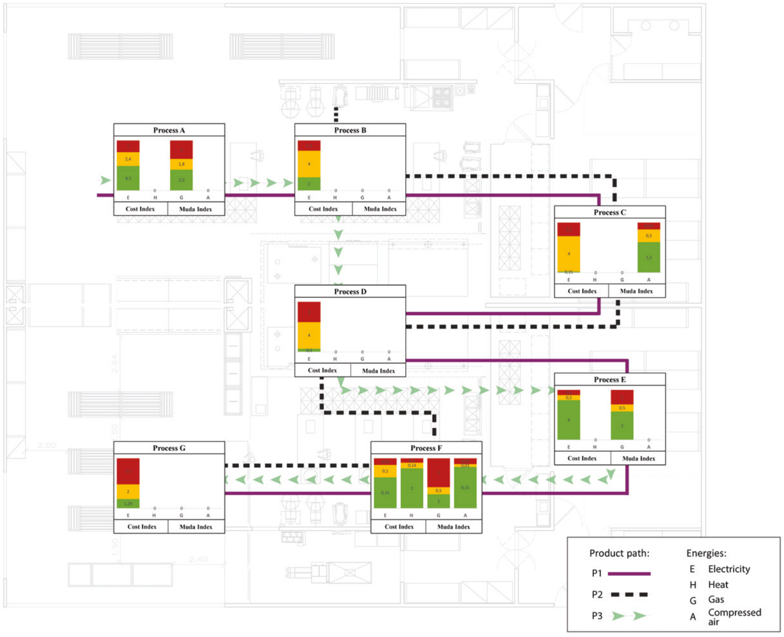


Figure 3.4: Example of Energy value map

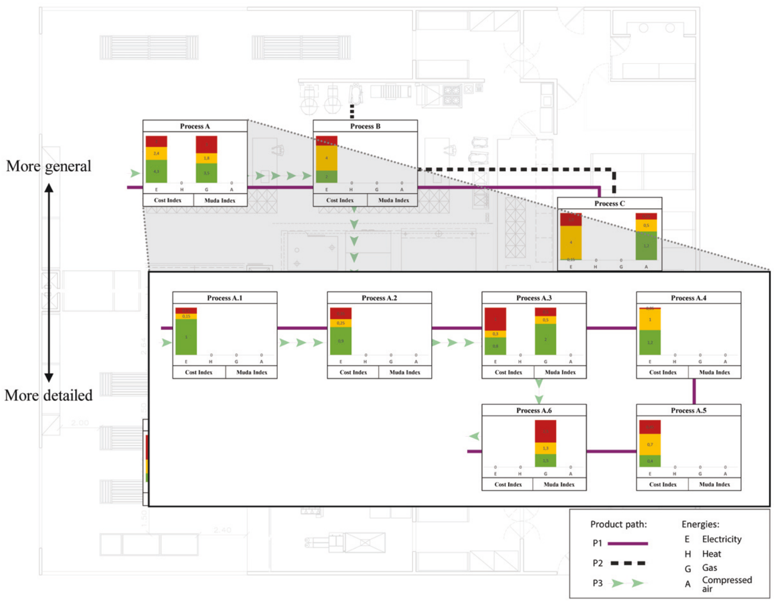


Figure 3.5: Hierarchy of the Energy value map

3.4 Improvement strategies definition

This phase allows to define the strategy for improving the manufacturing process. Once the critical situations and low efficiency process/machines are highlighted, an action plan is developed, primarily aiming at eliminating the waste of energy and decreasing the consumption of non value-added energy.

The method supports the user to identify the corrective actions and to elaborate the action plan.

3.4.1 Corrective actions identification

The corrective action describes a solution approach that aims to eliminate inefficiencies and improve energy performance. It is intended as an energy efficiency measure that may include technological, planning, behavioural, economic, and organizational changes.

As introduced in Equation 2.2, energy efficiency is defined as the ratio between an output and an energy input. Within this definition, the goal is to reduce energy consumption while maintaining the useful output. This means that a corrective action should not generally include a decrease in process output, although it may have this effect in a specific use case.

To support the user, corrective actions include both measures that directly influence energy consumption and measures to improve the organisational matters. An example of a direct action is the usage of energy-efficient motors in a machine, while measures to support the organisation are the use of an energy monitoring system that regularly checks a machine's energy consumption or the introduction of lean methods and tools. The aim is to provide the user with more approaches that can improve the efficiency of the production process.

Therefore, a literature review is carried out to identify corrective actions. Scientific articles reporting energy management tools and industrial applications aimed at eliminating and minimizing energy waste are analysed. Also documents and manuals for practitioners such as lean strategies and practical approaches to create a green value stream (Cherrafi et al., 2016) and guidelines such as BREFs (2009) or similar (e.g., Schorcht et al. (2013); Suhr et al. (2015)) are analysed. The most used energy efficiency measures are extracted from these documents.

After identification, the corrective actions are categorized according to specific criteria. The assessment criteria result from the analysis of scientific literature on energy efficiency implementation and applicability in factory management. They are: *Energy saving*, *Initial investment*, *Technical feasibility*, *"Human" feasibility*, *Uncertainty of results* and *Impact on production* (Table 3.2).

Table 3.2: Assessment criteria to classify corrective actions

Criterion	Note
Energy savings	*Amount of saved energy after implementation of a corrective action*
Initial investment	*Starting amount of money needed to implement a corrective action*
Technical feasibility	*Technical possibility of developing a corrective action with internal resources*
"Human" feasibility	*Possibility of developing a corrective action with internal human resources*
Uncertainty of results	*Lack of reliable data on the result of the corrective action implementation*
Impact on production	*Modifications to the production flow or to the process management*

The energy efficiency measures are classified through the involvement of a team of experts which is composed of two production managers, two plant managers, and an energy manager. In the evaluation, each specialist analyses the impact of each corrective action on the defined criteria. A 5-point scale ranging from *Very low* to *Very high* impact is utilized in the assessment (see the linguistic variables on Table 4.1).

Corrective actions have been then described based on other characteristics (Table 3.3). The categorization with these additional attributes allows to create homogeneous groups of energy efficiency measures where to look for the most suitable corrective action.

Table 3.3: Attributes to describe energy efficiency measures

Attribute	Measurement type
Type	Nominal
Objective	Nominal
Boundaries	Nominal
Energy type	Nominal
Specificity	Nominal
Pay-back time	Metric, ordinal, and qualitative
Internal rate of return	Metric and qualitative

The first attribute is the type of corrective action. The efficiency measures are classified as real time, off-line, or both. If the corrective action permits the rapid intervention on the ongoing anomaly, then it is classified as real time.

If, on the other hand, the measure provides for an intervention that can be carried out subsequently to the anomaly detection, then the measure is defined as off-line.

The energy efficiency measures are further classified according to the technical and organizational aspects. They are catalogued according to the objective (e.g., product-oriented, technical and organisational actions) and the boundaries (e.g., efficiency measures for the plant, production line or single machine).

Another classification is made to describe the applicability of the corrective action. This includes the energy type (e.g., electricity, heat, gas or other) and the specificity of a measure (i.e., whether it is specific for a sector or may be applied industry-wide).

Another important dimension of a corrective action concerns the relationship between costs and benefits. The costs for realizing a measure are influenced by the initial investment and maintenance costs. These effects may need to be considered during the entire measure duration. Corrective actions range from short-term ($<$ 2 years) through medium-term (2$\div$5 years) to long-term ($>$ 5 years) duration. The direct benefit is quantified as energy savings together with emission and/or waste reduction. In addition, increased productivity or reduced maintenance needs are also considered as benefits. The cost-benefit ratio is economically assessed through the pay-back time or the internal rate of return.

Table 3.4 provides an excerpt of the corrective actions subdivided according to the Lean classification. For each type of activity, some of the corrective actions identified and separated in conformity with VA, NVA and W are reported.

Table 3.4: Classification of corrective actions for the energy efficiency improvement (excerpt)

ACTIVITY	CORRECTIVE ACTIONS		
	VA	***NVA***	***W***
Processing of compliant products	◇ Maintain, refurbish and retune equipment ◇ Optimize process parameters		
More production than required			◇ Optimize production planning ◇ Kanban/Pull
Inventory of products, materials, energy		◇ Energy efficient warehouse ◇ Reuse/Recover	◇ Avoid unnecessary storage ◇ Just In Time
Production of non-compliant products			◇ Poka-Yoke ◇ Six Sigma ◇ Visual Management
Performing processes that are not required or with inappropriate techniques			◇ Choice of more adequate production technology ◇ Replace and retire obsolete equipment
Machinery setup		◇ Single Minute Exchange of Die ◇ Minimize energies requirements during setup	
Movement of materials or products		◇ Optimize layout and workflow ◇ Energy efficient transporter and handling system	◇ Avoid unnecessary movements ◇ Just In Time ◇ 5S
Movements of man or machine		◇ Optimize layout and workflow	◇ Avoid unnecessary movements ◇ 5S
Transport of energies		◇ Avoid unnecessary demand ◇ Optimize layout ◇ Reuse/Recover	◇ Avoid system losses
Corrective maintenance			◇ Total Productive Maintenance
Preventive or predictive maintenance		◇ Advanced process control	
Waiting		◇ Minimize necessary energies requirements in standby mode ◇ Visual Management	◇ Avoid unnecessary energies requirements in standby mode ◇ Just In Time

3.4.2 Definition of the action plan

After identifying and classifying the corrective actions, the next step is the definition of the action plan.

An action plan is a document that lists the steps must be taken in order to achieve the target established in step 1 of the method. It defines the necessary resources, prioritizes interventions and formulates a time-line for when specific tasks need to be completed. All stakeholders, from energy managers to technical, finance and production managers, must be involved in the definition of the action plan. The sharing of knowledge leads to better ideas and results. The established working group prioritizes the corrective actions and schedules them on the basis of time, resources and costs.

An ideal process requires and consumes only the resources needed to VA activities. However, in real contexts this limit cannot be reached. Therefore, the objective of this step is to define an action plan to eliminate the W energies, to reduce the consumption of NVA energies, and to maximize the energy efficiency of the VA activities, diminishing the cost of production and the environmental impacts (Figure 3.6).

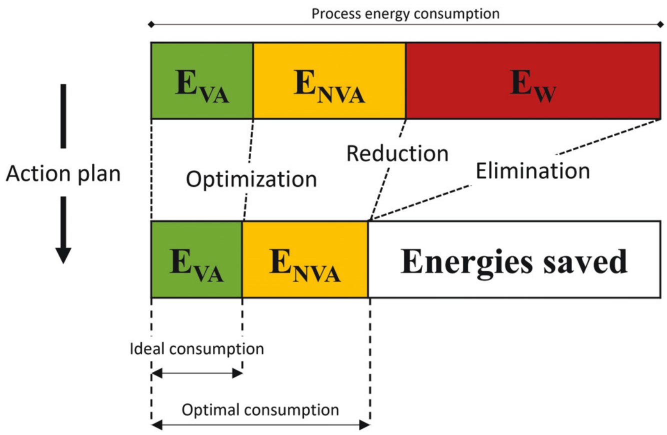


Figure 3.6: Optimization strategies aim

The workflow to define the action plan is shown in Figure 3.7. Once identified the main hotspots through the map analysis, each inefficiency should be investigated to identify possible causes and set improvement strategies. A Pareto analysis, based on MI, could support the identification of 20% of processes that need to be addressed to reduce the 80% of energies consumption not related to VA activities. It consists of the construction of a Pareto diagram according to the following steps:

1. List each process with its associated MI;

2. Calculate the MI% for each process k as follows:

$$MI\%_k = \frac{MI_k}{\sum_k MI_k} \tag{3.9}$$

3. Sort the processes in descending order placing the one with the highest MI% first;

4. Calculate the MI% cumulative values by adding each MI% to the sum of its predecessors;

5. Plot a bar for each process and the MI% cumulative values (horizontal axis: process; left-hand vertical axis: MI; right-hand vertical axis: MI%);

6. Draw a line at 80% of the MI% cumulative value onto the x-axis. This point on the x-axis separates the important causes on the left and less important causes on the right.

The Pareto analysis also allows to identify the important causes by process and energy simultaneously. In this case, each couple process (k) - resource (i) must be listed and the relative MI and MI% must be calculated as follows:

$$MI_{ki} = c_i \times (E_{\mathrm{NVA}i} + 2 \times E_{\mathrm{W}i}) \tag{3.10}$$

$$MI\%_{ki} = \frac{MI_{ki}}{\sum_k MI_{ki}} \tag{3.11}$$

At this point, for each identified cause one or more solutions are defined. The selection is carried out among the corrective actions identified in the previous phase. Through the correct classification and knowledge management, the method supports the user in the choice of the most appropriate corrective actions for the identified criticality.

Then, corrective actions have to be preliminary contextualized and evaluated on the basis of their impact on the reduction of energy consumptions and the relative investment scale.

Actions with high impact level and low investment level are preferred. However, before the effective implementation, their feasibility and cost-benefit ratio have to be preliminarily evaluated. In case of positive feedback, they can be implemented, otherwise, a further analysis is required.

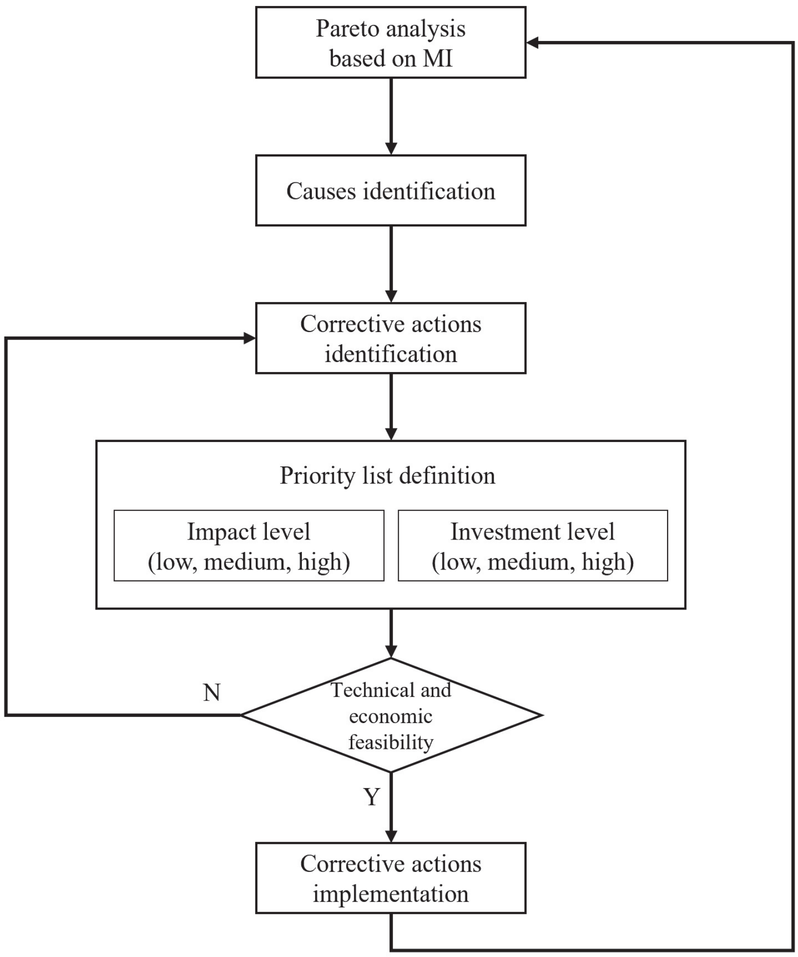


Figure 3.7: Improvement strategies definition process

3.5 Implementation

Once the action plan is defined, the implementation phase allows the realization of the programme in the manufacturing system. The actions with high priority and low payback time are implemented first. The corrective actions should cover all aspects of the production process: machinery, organization and human resources. They aim to eliminate inefficiencies and correct the causes of the problems.

Moreover, the implementation phase includes checking and performance evaluation activities. In this way, the company monitors the effectiveness of the action plan in achieving the set objectives in terms of energy reduction, cost reduction and environmental impact reduction.

3.5.1 Implementation and operation

At this stage, the activities which were determined in the action plans are implemented. As already shown in step four, it is necessary to form an energy efficiency team that is responsible for setting up, maintaining and checking the intervention. It is not sufficient to just appoint an energy manager, but all stakeholders must be involved in the energy team (e.g., production manager, worker, lean manager, technical department manager, etc.).

The team supports the implementation of the corrective actions. When they do not require a financial investment, they relate to organisational changes, for example, establishing responsibilities, a systematic data acquisition, the switching-off of machines and devices when they are not being used. Even adjusting energy supply contracts falls under this category. In particular, this type of interventions, such as simple changes in the behaviour of the employees towards energy, can lead to energy and cost savings of up to 50%. However, the problems during the implementation process are not be underestimated and well-defined responsibilities should be determined. When introducing measures that require investment, it is important to include suppliers and sub-contractors in order to realise the greatest possible savings potential.

The following aspects need to be considered to ensure effective implementation of corrective actions.

- Securing the necessary resources for implementing the intervention. Top management must guarantee the availability of required technical and financial resources which will ensure a smooth implementation of measures from the action plan. Additional human resources are of particular importance during the implementation phase.

- Raising awareness and training. After having defined responsibilities, it is necessary to find out whether all affected employees have the skills and

competence required to conduct their tasks in the field of energy management. This applies to the energy management team as well as all other relevant persons.
Raising and building awareness are important prerequisites for the success of the implementation of corrective actions in the company. Raising awareness can be achieved through several approaches (e.g., provide tips on how one can save energy and/or communicate achievements, through information campaigns and/or info screens) and it is important to motivate the employees to participate.
In addition, appropriate training leads to the establishment of the relevant and necessary competence in the company, as well as to creating awareness of the importance of energy management among individual employees. Training features direct technical aspects, like introductory training for using a new technology, or it can also include training measures which are indirectly related to energy (e.g., in the field of communication or project management). Apart from concrete professional training measures for individual employees, you should prepare training programmes for the conscious use of energy in the company.

- Communication and documentation. Effective communication is an important prerequisite for the successful implementation of corrective action. Informing employees on a regular basis increases their motivation to actively participate. In order to continuously improve the productive system, it is not only important to raise awareness among employees about the importance of energy management, but also a company culture needs to be established, one that enables workers to actively put forward suggestions for improvement and which motivates them on all levels. Apart from communicating to raise the general awareness of employees, it is important to regularly communicate the results of measurements and the energy indicators among all stakeholders.
All key elements of the analysis should be captured either on paper or electronically and then be recorded. The documents should be easily accessible and filed in a systematic manner.

- Operational control of all the processes. In the implementation of the corrective measures, all company processes must be examined in order to identify any inefficiencies created during the modification. This includes the procedures and processes (e.g., auxiliary systems and all connected processes), maintenance of facilities, installations and equipment, buildings, purchasing, procurement, as well as the energy consumption of all the commodities and assets used in the company.

3.5.2 Checking

The last phase of the method aims to monitor and verify the effectiveness of the implemented corrective actions. The establishment and maintenance of operational procedures and controls helps the company ensure it is controlling energy use and adhering to the policies, objectives and targets established in the first step (see Section 3.1). The design requirement in the previous phase requires that all new, modified or renovated facilities, equipment, systems and processes that the organization builds or implements that have a significant impact on energy use must undergo an energy performance evaluation.

According to the continuous improvement process and after the implementation of the corrective actions, a new data collection and analysis must be carried out to evaluate the achieved benefits in terms of energy efficiency and cost.

A frequent and regular comparison between the expected and actual energy consumption makes it possible to detect inefficient use of energy promptly. In any case, the areas of intervention and all the other relevant factors for energy consumption must be monitored (see Section 3.2). Depending on the type of intervention and organisation, the energy consumption of processes, compressed air, heating or lighting, for example, should be measured. The typical time period depends on the type and size of the organisation and individual facilities. Measurements can be made as real time measurements, or be carried out in monthly or even rarer intervals.

After the measurements and data collection, the indicators specified in the third step (see Section 3.3.1) must be redetermined. The percentages of energy consumed by VA, NVA and W activities and the two indicators (i.e., CI and MI) have to be recalculated. Then, the data is displayed in a new energy value map (see Section 3.3.2). In this way, the energy efficiency of the improved manufacturing system is defined. The map will make it possible to compare the obtained results and analyse if the implemented actions have eliminated or reduced inefficiencies. It will also allow to discover potential non-conformities compared to the expected results (e.g., a process not involved in the improvement that reduces its energy efficiency).

Chapter 4

Smart Energy Value Mapping tool

The methodology to assess the energy efficiency of a production system, presented in Section 3, has been implemented in a software tool called "*smart Energy Value Mapping*" (sEVM).

The purpose of the sEVM tool is to support companies in the continuous improvement of energy performance. Automatic and continuous process data acquisition and data elaboration allow to simplify the tasks that the user has to address in the application of the method. It allows identifying and characterizing the energy flow to multiple levels (machine, line, plant) and detecting its value-added component. Moreover, it allows to suggest a series of real time/off-line corrective actions to eliminate wasteful activities and reduce non value-added activities, from an energetic point of view.

After a brief explanation of the system architecture, this section is completely dedicated to presenting the sEVM tool framework. The data structure, databases, logics and algorithms and, finally, the user interface are described.

4.1 System architecture

The sEVM tool consists of four parts: *i)* the connection with the physical shop floor, *ii)* the cloud data center, *iii)* the web-based platform and *iv)* the analytics module. The cloud data center represents the repository of all the data needed for the analyses. The analytics module is able to use the collected data, calculate the key performance indicators and build the easy to visualize and interpret process boxes and resource value maps. The input and output data can be efficiently managed through the web-based platform that is essentially the user interface of the system.

The architecture of the tool is general purpose and designed as a flexible solution that can be and applied in different manufacturing sectors with their requirements. At the same time, the tool can ensure new developments and future trends. In addition, the tool has been thought to make it embeddable in any other IT system. The architecture of the tool are shown in Figure 4.1.

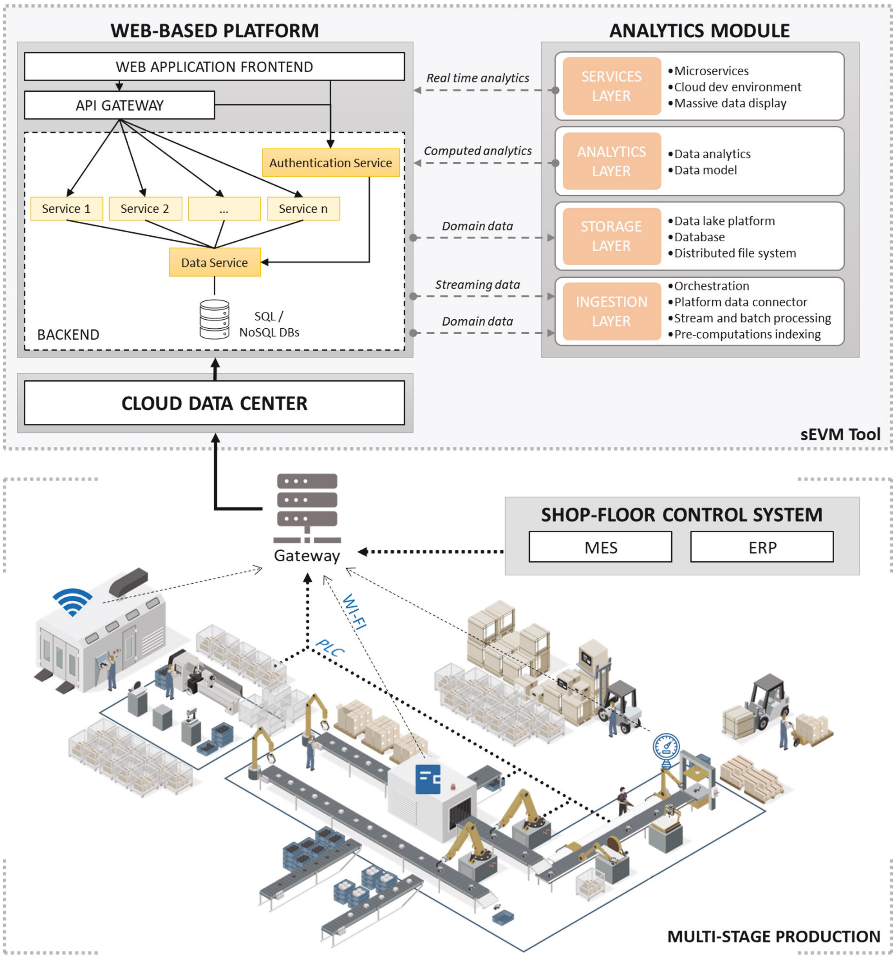


Figure 4.1: Architecture of the sEVM tool

Hereafter, the four main components of the tool (*multi-stage production*, *cloud data center*, *analytics module*, and *web-based platform*) are described in more detail.

Multi-stage production The first module consists of the shop floor where real production takes place as the creating point of manufacturing data. Machines and workers perform the work assigned for achieving goals under given process planning and configurations. They simultaneously output many operation and sensor data that involve resources, planning, control, monitoring, and metrology.

Input data include energy consumption data, the status of the production process (e.g., wait, maintenance, failure) and the process parameters (e.g., input/output pieces, pressure, temperature). The latter can be collected through direct connection with the equipment, IoT devices/sensors (e.g., proximity, temperature) and the company production control systems (e.g., Manufacturing execution system -MES, Enterprise resource planning - ERP).

Data collection systems, like supervisory control (e.g., PLC) and data acquisition systems (e.g., by wireless network protocols), gather and transmit such collected data into a cloud data center. The gateway represents the "bridge" among the rough data, coming from production processes and from other company repositories, and the cloud data center. Finally, data collection systems include softwares that receive and store a time series of data samples or events and act as a bridge between a machine and a client application, support efficient data collection.

Cloud Data Center The Cloud Data Center, constituted by a set of interconnected non-physical repositories that allow to fully exploit the cloud potentialities, is an information center that stores and exchanges production data. Collecting data in the cloud data center promotes the reduction of information asymmetry traditionally found with different sensors and systems. In this way, data are consistent with each other and allow to generate an in-depth and integrated knowledge of the production process.

The module receives raw manufacturing data and their metadata from the physical shop floor and stores them structurally in terms of designated attributes. It then returns datasets when queries are called by the web-based platform. Its main work is to store design and control data from manufacturing applications, to gather and store manufacturing data generated from the physical shop floor and to associate the collected data with the process data model. Thus, the web-based platform can manage information's flows coming from different sources, store them in multiple databases and extract significant information according to user requests.

It manages the acquired data by means of an excellent connectivity solution with the meters in the plant. Different communications protocols are implemented to collect data. The acquisition system can be adapted depending on the amount and typologies of data to be collected and managed. The tool allows customizing and configuring devices for monitoring the whole production plant with the level of detail as required. For example, it allows changing settings as acquisition time and data type.

Analytics module The tool is equipped with an Analytics module that gathers data from the cloud data center, processes them and, thanks to a set of algorithms, provides indications on energy inefficiencies and suggests the most proper corrective actions. These results are shown to the users through the web-based platform interface.

The module is aimed at data engineering and Big Data management (analysis, organisation, aggregation of data). It presents a unified and data-stream oriented platform and uses cutting-edge technologies to manage the entire data analysis and implement the proposed methodology.

It exploits statistical mathematical logic for the validation of data collected by sensors to exclude the ones that could invalidate subsequent data processing activities (e.g., instrument failures, calibration in progress, anomalies). Then, it is responsible to convert these data into useful information and allows a clear and detailed view of the energy efficiency of the process through the automatic generation of the energy value map and the calculation of the relative indicators. It supports the plant manager in the real time identification of energy inefficiencies and the decision-making. In fact, this module is also responsible for autonomously suggesting intervention and reaction strategies to eliminate waste and improve energy performance. At the same time, output data and indicators generated are stored in the repositories of the cloud data center as reference knowledge for future analyses to foster a continuous improvement approach.

Web-based platform The Web-based platform can manage information flows coming from different sources, store them in multiple databases, and extract significant information according to user requests. Information is displayed simply and intuitively thanks to a user-friendly and easily navigable graphic interface and the access to them is managed according to the user class permissions that foresee three main users: (*i*) plant manager, (*ii*) energy manager, and (*iii*) operators. The platform has been designed and developed to be accessible from multiple devices, from fixed workstations (PCs, notebooks), or directly in the workshop (tablets, smartphones).

The Web-based platform architecture is based on micro-services and a script interpreter that allows to customize the applications and to make on-line changes without the need to stop the systems during production. It exploits modern, open source, and production-oriented technologies and supports asynchronous computations and multi-language integration, which ensure high flexibility and reliability. The platform consists of the development of data management applications, with the ability to control all types of data.

As shown in Figure 4.1, the platform consists of the following three main elements: Frontend, Backend and API Gateway.

Each frontend page only interacts with the API gateway and the authentication service, while all the other interactions take place in the backend, which is the core of the platform. The frontend displays the full functionality of the platform. It is compatible with all major web browsers, enables the interaction between the tool and the user. It allows performing the following actions:

- Managing databases to update the data related to plant layout, machines, products, production scheduling, energy supply contract;
- Setting thresholds for sending warnings;
- Consulting and managing notifications (i.e., ignore, examine);
- Performing real time and off-line analysis by tables, graphs, maps and indicators (e.g., compare current trends with historical data, consult massive data, visualize aggregate data);
- Defining an action plan by consulting, comparing and selecting the intervention strategies.

The backend is a combination of databases and microservices (e.g., navigation, notification, event) structured so as to facilitate and optimize data management. This element has the function of communicating with the environments connected to microservices. Furthermore, it can manage performance in situations of errors on microservices. Also, it includes a component for asynchronous interactions.

Finally, the API Gateway acts as a single-entry point for client requests to the backend, accepts and turns them to the specific micro-service, and creates a single point for the authentication management.

The Web-based platform and the Analytics module have a very high level of data integration, based on different levels of data processing:

- Ingestion layer: streaming data (e.g., logs, user interactions, real time events) and domain data with specific preprocessing needs (e.g., geolocalization, time stamp);
- Storage layer: domain data (e.g., metadata, classifications, business entities, workflows);
- Analytics layer: computed analytics to be moved into the Data Warehouse (e.g., statistics, diagnosis, predictions);
- Services layer: real time analytics to be presented in the dashboard and user interface (e.g., analytics alerts, reports).

4.2 Tool framework

Figure 4.2 presents the tool framework and the general workflow illustrating how it works and supports stakeholders in improving the energy efficiency of the production process.

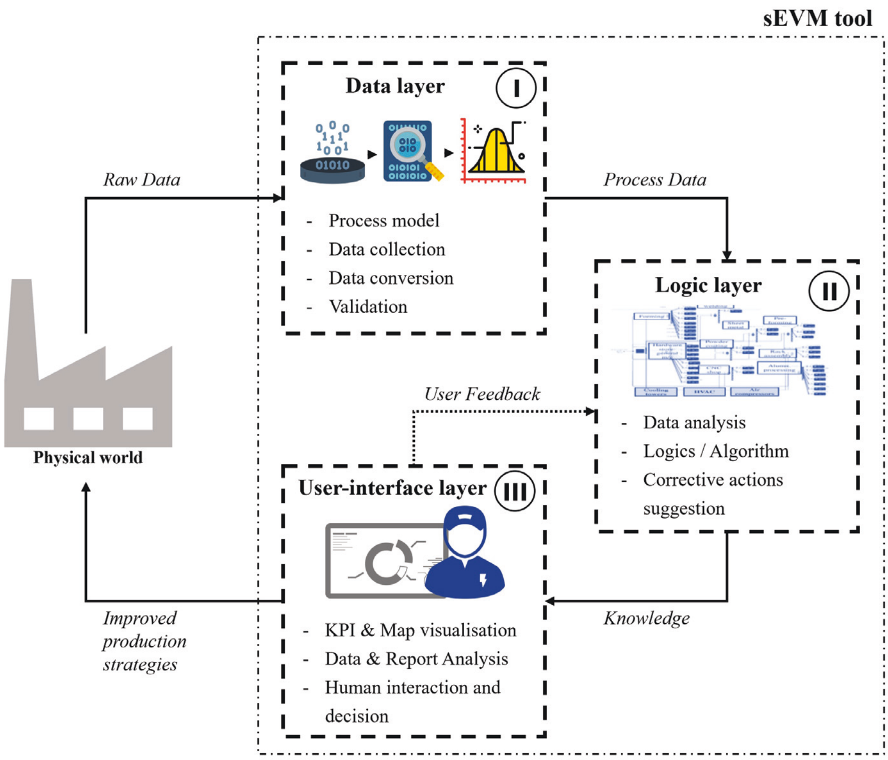


Figure 4.2: General framework of the sEVM tool

The first step is the configuration of the data model. The tool is filled with knowledge about the involved manufacturing systems and processes as well as the energy consumption measurement devices and other available sensors. The form and frequency of data collection from these devices are defined, and energy consumption parameter models are set up to calculate the current energy consumption. Finally, corresponding rules are defined to specify the acceptable ranges of context-aware energy consumption parameters. During the manufacturing process (Step 2), the runtime energy use is constantly monitored by calculating the current energy consumption values and the KPIs. The calculated values are compared with the values specified in Step 1, using rule-based reasoning to try to detect any excessive use of energy. In the third step, if the energy use parameters monitoring and the analysis module have detected an excessive energy use, it signals the occurrence of an anomaly. A warning is generated to notify stakeholders and the information about the detected problem stored in the common repository.

In detail, the sEVM tool consists of three main layers. The Data layer (*I*) retrieves production data from the physical world on a regular basis and converts it into inputs for the Logic layer (*II*). The data is then processed to determine the energy efficiency of the manufacturing process and detect anomalies. The results of the data analysis are shown to users in the User-interface layer (*III*). Through user decision support improvement actions are initiated and conducted.

After the data model configuration, the tool collects and orders the raw data of the physical process and, after a first validation, elaborates the process data to calculate the energy efficiency. Then, the developed knowledge is visualized through the graphical user interface. If no anomalies are detected, the tool carries on monitoring the process by repeating the steps. Otherwise, it activates the analytics service that identifies the problem and suggests to user the possible solution strategies. Through the interface, the user validates the analysis results and selects the most appropriate corrective action. At this point, the corrective action is implemented on the physical process and the efficiency of the intervention is evaluated by further tool's iterations. Moreover, the tool stores the user's feedback and associates it to the identified problem. In this way, the database is constantly updated and the tool fits the needs of the analysed process.

The sEVM's main user is the energy manager who uses it to evaluate energy use and design corrective actions that increase efficiency and reduce energy-related costs. The tool supports both the energy consumption monitoring phase and the efficiency analysis of the production process, as well as the decision-making phase. At the first tool implementation, the energy manager models the production system and sets the tool's parameters (i.e., characterizes the activities, selects indicators, sets threshold values, etc.). In the use phase, the energy manager analyses the data collected and processed by the tool, receives the warnings of the anomalies detected and selects the most appropriate corrective action.

The tool can also be used by all other user who are involved in the production process, and not only by the energy experts. Data is available to the operative users from production management, facility management, as well as operative and maintenance staff. Each stakeholder has access to the tool to acquire information about the energy properties or to develop knowledge about how to increase efficiency. Each one of the users has a different perspective on the process, and the engagement during the decision-making and action plan implementation allows for improved outcomes. In addition, the development of graphical interface screens with only aggregated data and main indicators (i.e., Dashboard and Report screen) allows all stakeholders to use it, even without specific skills in the energy field. The data and report visualization can be useful both in the decision-making process and company management, as well as to the process manager or worker to optimize production.

4.3 Data layer

It serves the functions for data sorting, data storage, and input data feeding.

The Data layer collects all data gathered on the production process through an ingestion pipeline service that receives data from the factory's IT infrastructure including sensors, meters, PLC, SCADA, ERP and MES. It is a supplementary service since a clear separation from databases will avoid interference and data loss. It adds a timestamp to each cell and can keep previous versions, allowing applications to store and access the historical datasets. This capability makes it possible to collect easily and quickly up-to-date data into collections based on metadata. Then, the data is sorted and aggregated by the storage level which makes them available for the next processing step.

The main functions are:

- Data model configuration. The configuration of the production model structure is carried out by compiling the Configuration databases. The definition of the relations between the different items allows to create the virtual model of the production process by which the data are organized and the subsequent analysis steps are carried out (see Section 4.3.1).
- Data collection. The input data is stored in dedicated Data databases according to the data model configuration.
- Data conversion. If necessary, the tool converts the collected data into a appropriate format for the next processing steps. Data that is not compatible with the analysis are converted using the typical database conversion functions such as, for example, the transformation of a string into a date and time, and the conversion of a text data into a numeric string.
- Validation. The input data, after being saved, are subjected to an automatic validation process, which aims to eliminate any outliers through the application of some rules. In case of instrumental errors generated by sensors and/or meters, it delete them. Through the comparison with the historical series, the tool excludes those data clearly wrong (e.g., negative value of energy consumed) from following analysis to not compromise the results. If instead a single data is missing for a communication interruption with the device, the tool proceeds with a linear interpolation and reconstructs the missing item on the basis of the previous and next data.

4.3.1 Tool databases

A central part of the Data layer is represented by the databases that constitute an information hub for storing and exchanging production data. This warehouse receives the raw production data and their metadata, and stores them structurally in two kinds of databases: Data database and Configuration database.

The former are the databases where the application data physically resides. The data provided by the various sensors and systems of the production process are stored in dedicated structures and then used for data analysis activities. They also contain other needed data, such as the processes database, the machine database and the corrective actions database (Section 3.4.1).

A Mongo DB is implemented for storing the process data. It is a document store type of NoSQL DB which provides flexibility, horizontal scalability and is open source (MongoDB, 2016). It supports the storage and the efficient management of Big Data originated by physical and composed measurements on the environment and on manufacturing systems. In addition, MongoDB allows to incorporate any kind of data and analyze data of any structure directly within the database, giving the results in real time.

On the other hand, a SQL Database is employed to store process and machine data, and for Configuration databases. It is made up of a collection of tables on which structured data and relationships are stored (ISO, 1992).

Configuration databases are structures where the logical representation of data is configured, limit values are set and the stored procedures that guide the events that occur during the use of the application are developed. The structure of the knowledge repository has been developed to be flexible and adapt to any production context.

The main Configuration database concerns the structure of the process data model. The Process model DB (Figure 4.3) contains the data required for the modelling of the production process and consists of the following tables:

- Process type: it stores all the process type classes (e.g., handcrafted batch production, automated batch production, automated continuous production, etc.);

- Work sequence: it contains the information on the sequence of working tasks that are carried out through the production process. It reports the information of the involved machines, the potential set-up phase and the valorization of the working activity. The valorization allows to allocate the energy consumed according to the lean approach and is based on the Table 3.1 and on the machine's energy states. In detail, the energy states are identified as off, ramp-down, stand-by, maintenance, idle, set up, ramp-up and processing.

- Machine tool: it consists of data on the machines used in the production process. It includes information on the family and typology of machines (e.g., lathe, milling machine, grinder, etc.), the parent process, the location within the shop floor, the rating power, the year of construction and the mode of operation (e.g., constant, intermittent, variable, etc.).

- Parent process: it includes information about the structure and links between the various components of the production process. It defines the hierarchical structure of the production system and divides it into process/production line, department, plant and company.

- Features: it comprises all information related to the product features that affect process energy consumption. It reports the properties associated with the thickness, size of the product (e.g., width and length) and the material to be processed (e.g., aluminum, copper, carbon steel, thermoplastic polymers, etc.).

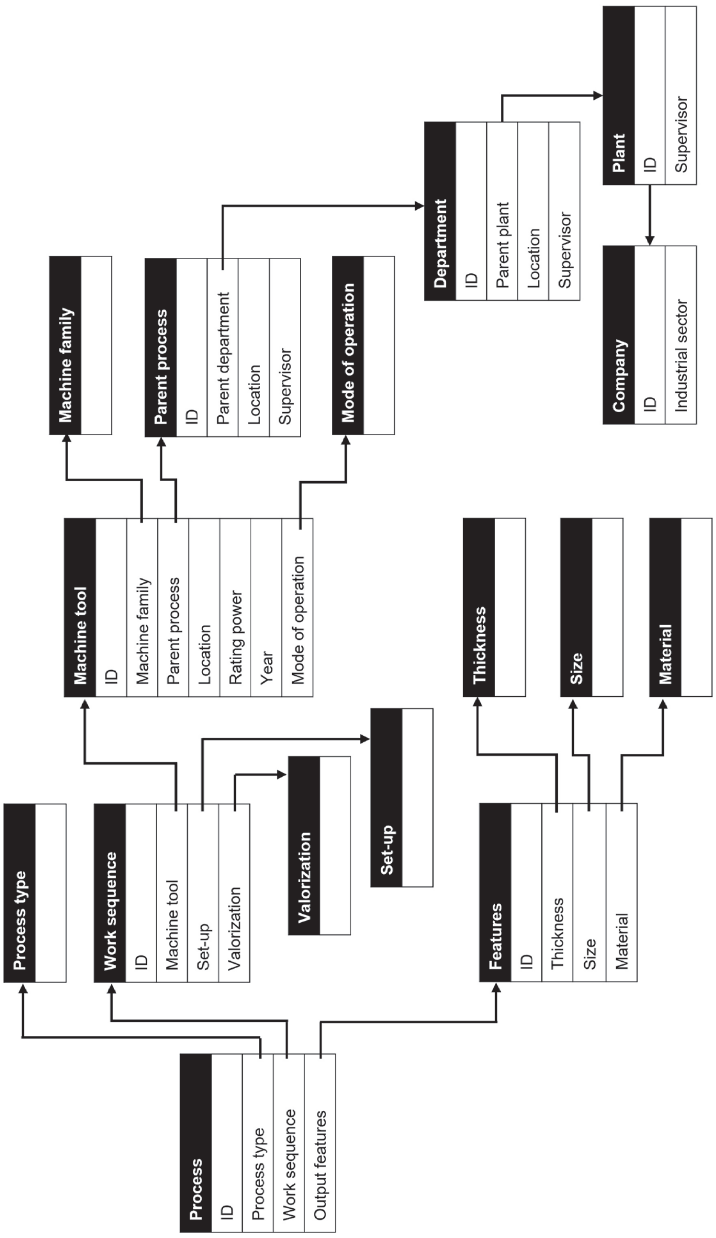


Figure 4.3: Process model DB structure

4.4 Logic layer

As a central part of the tool, the Logic level is based on a series of logic and algorithms to characterize energy and efficiency flows within a production system. The input data are automatically sourced from the Data layer and, on these it performs computation and analysis operations. The objectives are to support process energy mapping, calculation of indicators and KPI, and to assist the decision-making phase in case of anomalies.

It contains the logics and algorithms that allow to control the energy efficiency of the production process. In detail, it includes the algorithm for energy allocation and process mapping (Section 4.4.1), the decision-making algorithm for the identification of causes and corrective actions (Section 4.4.2) and the matching algorithm for the identification of the most appropriate corrective action (Section 4.4.3).

4.4.1 Allocation algorithm

The Allocation algorithm represents the data processing scheme of the tool (Figure 4.4). It starts by reading the active power of each connected meter and, based on the time interval, it calculates the energy consumed. The energy consumption E_j is calculated with the following formula, where P_j refers to the power demand [kW] of j^{th} process and t_0 - t_1 refers to the measurement time interval [h].

$$E_j = \int_{t_0}^{t_1} P_j \, dt \tag{4.1}$$

Then, according to the process model defined in the Data layer, it calculates the total energy consumed (E_{tot}) by the workstations, departments and plant as sum of the j^{th} components. In this way, it can display information about the energy consumption of the production process.

$$E_{tot} = \sum_{j}^{n} \int_{t_0}^{t_1} P_j \, dt \tag{4.2}$$

The sEVM tool examines then if the production process is currently working. It analyses whether the work shift has started by checking the MES data with the current time. If the process is idle or paused, the energy consumed is allocated as waste (W) energy.

If the work shift has started, the tool controls whether the process is generating value. First, it determines if the machining generates value by analysing the information contained in the Work sequence DB. Afterwards, it analyses the machine/task status data, detecting whether the system is working on a product or not. If the first choice shows that the process is not generating value and by the second, that it is not producing, the energy is allocated to W energy. Alternatively the energy is classified as non value-added (NVA) energy, since the machining processing is supportive to the core activity and does not generate value.

If, on the other hand, the process generates value and is producing, the energy is value-added (VA), otherwise NVA energy.

Finally, the tool analyses if non-compliant parts are generated during the production. If the output is not compliant, the energy consumed will be W energy, otherwise the previous valorisations are confirmed.

At this point, the tool calculates the different energy components and the indicators as defined in the Section 3.3.1 (see the formulas 3.4, 3.5, 3.6). The Cost index (CI) and the Muda index (MI) are calculated with formulas 3.7 and 3.8 respectively.

Other more KPIs are also calculated. The KPIs can be defined by the user during the data model definition, in order to customize the analysis to the existing company models. Firstly, the following KPIs are implemented: Specific Energy Consumption (SEC), Energy Efficiency (EE) indicator and Overall Equipment Effectiveness (OEE).

In detail, SEC_j represents the real usage of energy in production of goods or products. A low SEC_j value is indicative of company efficiency in manufacturing processes. It is calculated for off-line analysis in which longer-term measurements such as hourly, shift, daily, monthly or annual monitoring are analysed. In this case, energy consumptions are plotted against compliant production in a scatter plot at least for ten occurrences.
It can be calculated as:

$$SEC_j = \frac{\sum_j E_j\ [kWh]}{\sum_j Compliant\ production\ [n]} \tag{4.3}$$

EE_j is is the ratio between compliant production in a stable process under the common processing conditions and energy consumption.
It can be calculated as:

$$EE_j = \frac{\sum_j Compliant\ production\ under\ stable\ process\ condition\ [kg]}{\sum_j E_j\ under\ stable\ process\ condition\ [kWh]} \tag{4.4}$$

OEE_j is an indicator which represents how effectively a line/equipment produces in a defined time. It is calculated as the product of three separate components: Availability (A_j), that is the percentage of scheduled time that the

operation is available to operate, Performance (P_j), that is the speed at which the machine runs as a percentage of its designed cycle time, and Quality (Q_j), that is the good units produced as a percentage of the total units produced.
It can be calculated as:

$$OEE_j = (A_j \times P_j \times Q_j) \tag{4.5}$$

Where:

$$A_j = \frac{PPT_j - T_{stoppages_i}}{PPT_j} \tag{4.6}$$

$$P_j = \frac{Cycle\ Time_j \times N°good\ produced_i}{OT_j} \tag{4.7}$$

$$Q_j = \frac{N°\ good\ produced_j - N°scraps\ /\ reworks_j}{N°good\ produced_j} \tag{4.8}$$

- PPT_j is the Planned Production time;
- $\mathrm{T}_{\mathrm{stoppage}_j}$ is the down time loss due to breakdowns, setup and adjustments, change model and startup;
- OT_j is the operating time

The results of the elaboration are then shown through the graphical user interface.

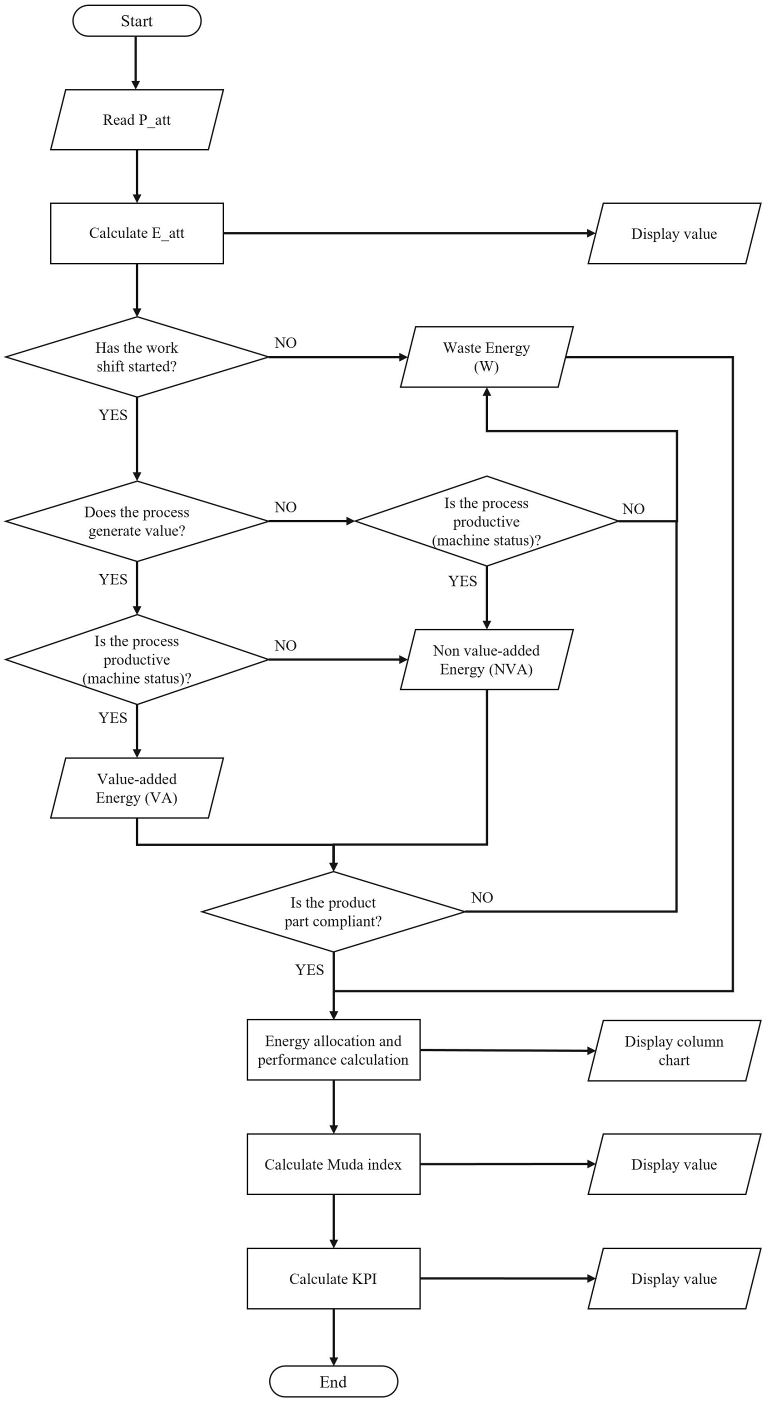


Figure 4.4: Allocation algorithm

4.4.2 Decision-making algorithm

The decision-making algorithm stands for the workflow of the tool to identify the causes of inefficiencies and corrective actions (Figure 4.5).

The algorithm starts by analysing the indicators and KPIs calculated in the previous section and compares them to the reference values of the historical series. At the beginning, the tool works with the MI indicator since it provides a measure of the energy not used to generate value and the process efficiency. However, it allows to extend the control to other indicators too. The objective is to identify irregular variations of the indicator and to omit the common ones. The common cause variations are considered to be an inherent part of the production process and cannot be changed without changing the process itself.

In detail, it monitors if the i^{th} sample of the indicator (χ) is compliant with the average process value. The reference value ($\overline{\chi}$) is calculated according to the formula:

$$\overline{\chi} = \frac{1}{n} \times \sum_{i=1}^{n} \chi_i \tag{4.9}$$

where $(\chi_1, \chi_2, \ldots, \chi_n)$ are the samples.

The upper control limit (χ_{upper}), and the lower control limit (χ_{lower}) are then calculated with the following formulas (Qiu, 2013).

$$\chi_{upper} = \overline{\chi} + \frac{Z_{1-\alpha/2}}{d_1(n)\sqrt{n}} \times \overline{MR}_{\chi} \tag{4.10}$$

$$\chi_{lower} = \overline{\chi} - \frac{Z_{1-\alpha/2}}{d_1(n)\sqrt{n}} \times \overline{MR}_{\chi} \tag{4.11}$$

The tool can monitor the indicator trend and detect the anomaly if one or more points are outside the area delimited by the control limits. At the i^{th} time point, if the i^{th} value of χ is beyond the two control limits, i.e.,

$$\chi_i < \chi_{lower} \quad or \quad \chi_i > \chi_{upper}\ , \tag{4.12}$$

then the indicator reveals that the process has an anomaly.

The tool also checks the *moving-range* of the indicator (labeled by MR_{χ}) to generate alerts to the operator. The average value ($\overline{MR}_{\chi}$) and control limits are calculated from the following formulas (Qiu, 2013):

$$\overline{MR}_{\chi} = \frac{1}{n} \times \sum_{i=1}^{n} MR_{\chi\, i} \tag{4.13}$$

$$MR_{\chi\ upper} = \left(1 + \frac{Z_{1-\alpha/2} \times d_2(n)}{d_1(n)}\right) \times \overline{MR_\chi} \tag{4.14}$$

$$MR_{\chi\ lower} = \left(1 - \frac{Z_{1-\alpha/2} \times d_2(n)}{d_1(n)}\right) \times \overline{MR_\chi} \tag{4.15}$$

Points outside of these control limits are signals indicating that the process is not operating as consistently as possible. If the i^{th} value of MR is above or below the limit value, then the process reveals an anomalous variation compared to the common variability of the production process.

The tool has a set of decision rules for detecting non-random patterns of the trend of the two parameters. According to these rules, the tool identifies an event if one of the following cases happens:

- One point is outside the three-sigma control limits;
- Two out of three consecutive points are outside the two-sigma control limits;
- Four out of five consecutive points are at least one sigma away from the center line;
- Eight consecutive points are located on one side of the center line.

If the test reveals an irregular value, the tool reports the event to the user and starts investigating the cause of the inefficiency. It begins by analysing whether the event is related to a work shift or a rest period.

If the production is idle, the tool identifies the most energy-intensive machine and determines whether it is necessary for the plant functioning. It reads the information contained in the Machines DB and, if the machine is not necessary, it is identified as the responsible for the inefficiency. If, on the other hand, the machine is essential for the functioning of the production process (e.g., cooling system for storing materials), it is excluded from the analysis and the tool starts again by analysing the other energy-intensive machines.

If instead the irregular value of the indicator is relative to a work shift, the tool analyses whether the production process has been interrupted. To identify the cause of the interruption, the tool analyses the data of the MES related to maintenance operations and the data on the machine status.

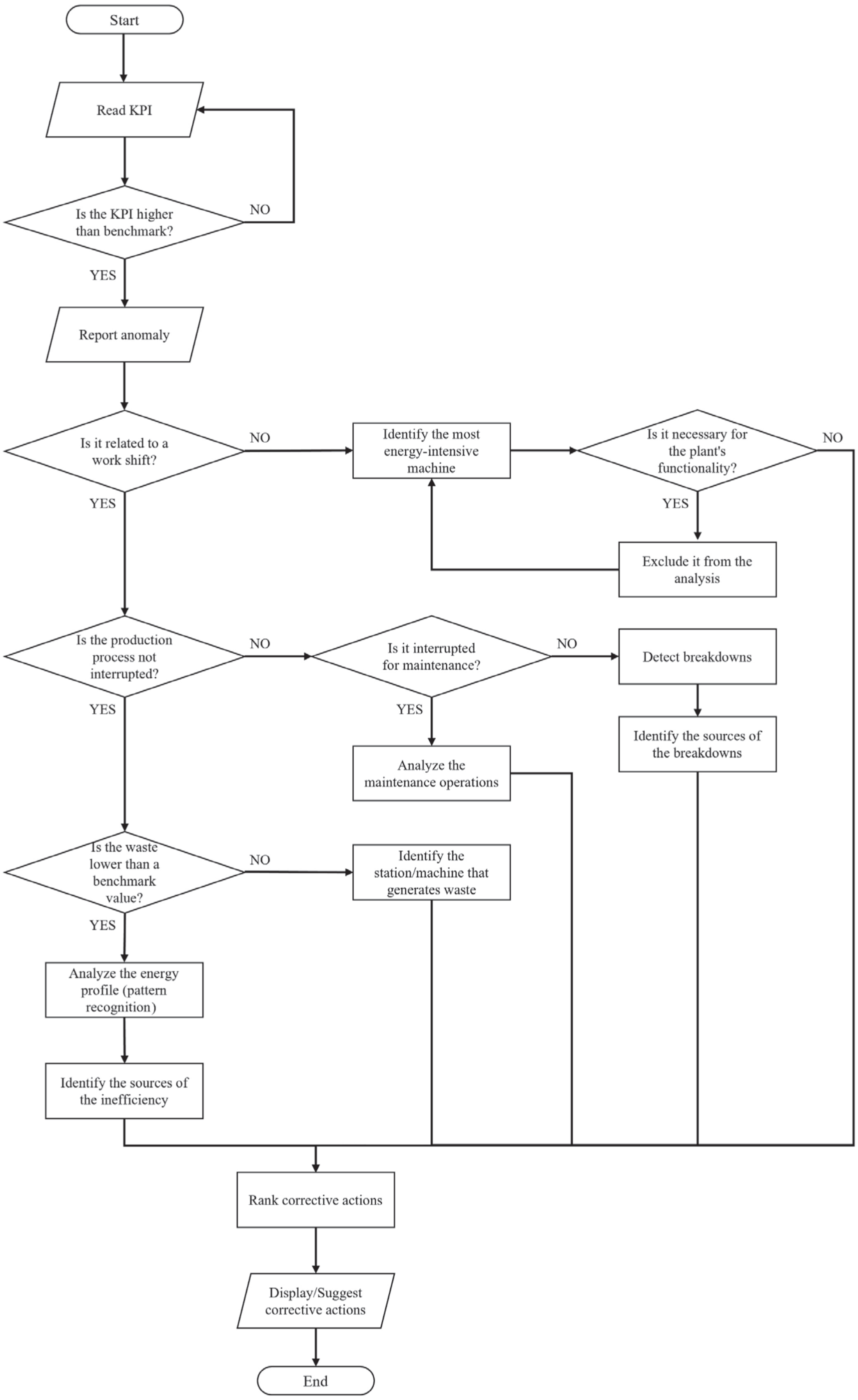


Figure 4.5: Decision-making algorithm

If there are no maintenance interventions, the production has been interrupted for process-related problems such as a lack of workpiece or discharge problem. The tool, after checking the previous machines status, identifies the cause of the inefficiency and the responsible machine, through the analysis of machine warnings. If there are maintenance interventions, the tool analyses the data of the intervention on the MES and, through the evaluation of the report, identifies the cause of the inefficiency.

If the event is related to a work shift and there are no interruptions, the tool analyses whether there are non-conforming or discarded workpieces. The tool compares the i^{th} value of the machine's non-compliant parts with the reference values of the historical series.

$$\phi \ > \ \frac{1}{n} \times \sum_{i=1}^{n} \ \phi_i \tag{4.16}$$

If the value of non-conforming parts (ϕ) is higher, then the tool identifies the responsible machine as the cause of the inefficiency.

If the tool does not detect any of the above conditions, it performs an energy profile analysis for the period considered and compares it with a reference profile. The tool uses Pattern Recognition algorithms to determine the cause of the irregular value of the indicator. The algorithms are burdensome from a computational point of view and therefore they are applied if none of the previous conditions are satisfied.

In detail, a 1-Dimensional Convolutional Neural Network (1D CNN) has been implemented. The CNN models are generally employed for image, video and audio recognition where multi-dimensional kernels are applied together with multi-dimensional inputs (Kiranyaz et al., 2021). However, in recent years, 1D CNN models have been developed for prediction tasks that involve time series, such as real-time electrocardiogram monitoring (Acharya et al., 2017), automatic speech recognition(Abdel-Hamid et al., 2014), motor-breakdown recognition (Ince et al., 2016) and vibration-based structural damage detection in civil infrastructure (Avci et al., 2021), with good performance results. Moreover, due to their moderate computational requirements, 1D CNNs have proved to be well-suited for real-time and low-cost applications especially on mobile devices (Kiranyaz et al., 2021).

The implemented 1-Dimensional CNN model has multiple layers and the data and kernels are one-dimensional vector. It employs the following operators: *a)* Convolutional Layer that extracts the characteristics from data; *b)* Max-Pooling Layer that shrinks the matrix by considering only the highest values; *c)* Flatten Operator that unrolls the values beginning at the last dimension; and *d)* Dense Layer that obtains a single output result.

The number of layers is defined by the dataset size and the parameters that the tool has to analyse. For the case studies considered, the 1D CNN has one input layer, two hidden convolutional layers composed by two consecutive pairs (Convolutional layer, Max-pooling layer) and two fully-connected layers (Flatten Operator layer and Dense layers). Figure 4.6 summarizes the structure of the 1D CNN model.

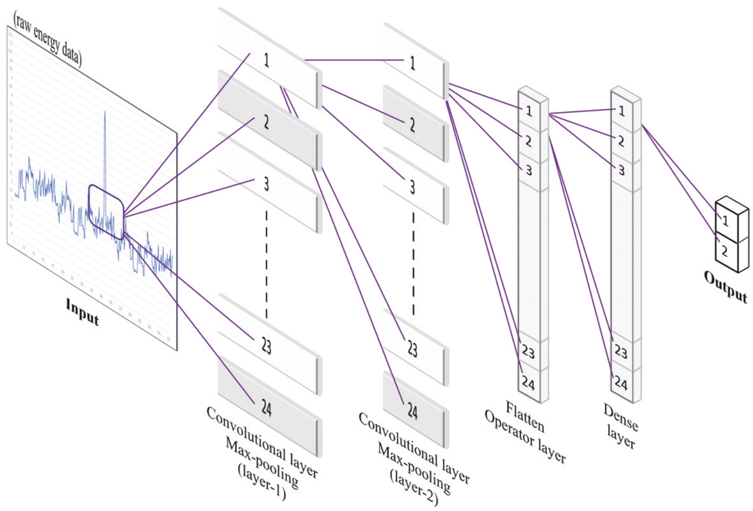


Figure 4.6: Structure of the 1D CNN model

The data required for training the CNN was are taken from manufacturing process monitoring. The data are acquired before the analysis phase and describe the energy use of the process under optimal operating conditions. The tool is able to identify the data points fall outside the norm, recognizing the irregular energy peaks and unusual consumption trends. Analysing them with the production data, the tool determines the cause and/or the equipment that generated the inefficiency.

After identifying the cause of the inefficiency, the tool makes a ranking of the most appropriate corrective actions using the matching algorithm for corrective actions defined in the Section 4.4.3.

Finally, it sends the warning to the user and shows the results of the analysis through the user interface. The information and data related to the anomaly, the cause of the inefficiency and the suggestion of the most suitable corrective actions are displayed.

4.4.3 Matching algorithm for corrective actions

The decision-making algorithm determines the cause of the inefficiency and identifies corrective actions based on the data collected on the production process. In the previous section, the domain of application of the algorithm is discussed regarding its structure and description. The goal of the algorithm is to identify the most appropriate corrective action for the notified event. This matching task is realized by the matching algorithm that takes into account the identified weights to detect the most appropriate energy efficiency measure.

The energy efficiency measures represent short/medium action approaches to reduce energy consumption and are linked with the inefficiencies identified in the process. After the decision-making algorithm detects the cause of the event, the tool determines the corrective actions associated with that anomaly. Among them, it applies the matching algorithm to define the most appropriate one.

The assignment task is realized by a matching algorithm that is based on the multiple-criteria decision-making. It uses the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) which considers the Euclidean distances of decision alternatives to ideal and negative-ideal solutions. According to this technique, the best alternative should have the shortest distance to the ideal solution and the greatest distance from the negative-ideal solution (Tzeng and Huang, 2011).

In this technique the weight of the criteria and the ratings of alternatives must be known accurately, although this does not reflect the production dynamics. Often, the information does not allow an accurate judgement since the data may be unquantifiable, incomplete and non-obtainable. To overcome these problems, the Fuzzy logic has been introduced by which the criteria weights and alternative ratings are given by linguistic variables, expressed by fuzzy numbers.

The concept of linguistic variable helps to deal with situations that are too complex or undefined to be reasonably described in conventional quantitative terms. A linguistic variable is a variable whose values are in textual terms. Rating is used to represent comparative importance values, which are then converted into triangular fuzzy numbers (Table 4.1).

Table 4.1: Linguistic variables for the ratings

Linguistic variable	Triangular fuzzy number
Very Low	(1;1;3)
Low	(1;3;5)
Medium	(3;5;7)
High	(5;7;9)
Very High	(7;9;9)

Figure 4.7 shows the steps of the matching algorithm to determine the most appropriate corrective action.

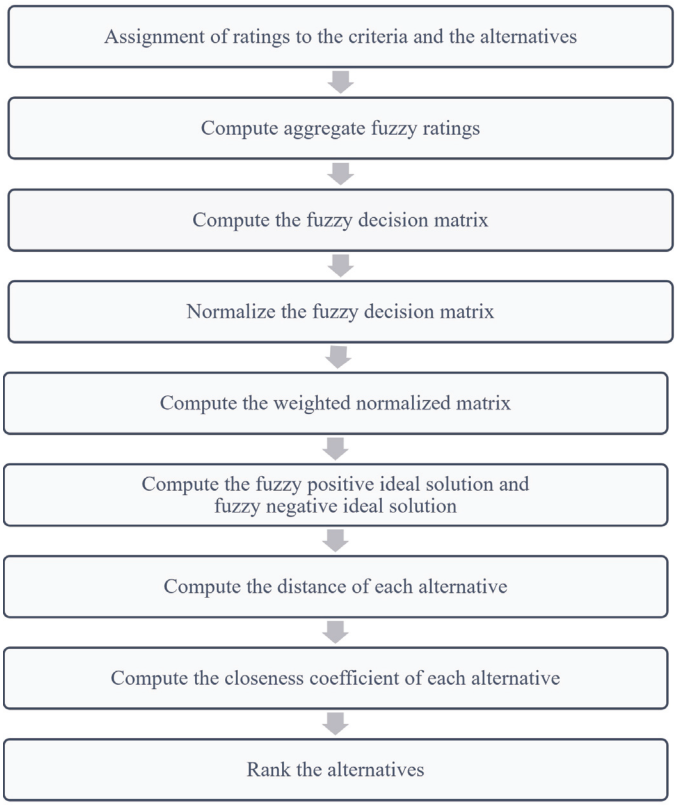


Figure 4.7: Steps of the matching algorithm for corrective actions

The main implementation steps of the algorithm are:

- *Step 0.* Assignment of ratings to the criteria and the alternatives.

  Before starting, the criteria defined in the Table 3.2 are classified with the purpose of determining their level of importance. The involved expert team (i.e., two production managers, two plant managers and an energy manager) determines the priority of each criterion using the linguistic weighting variables defined in the Table 4.1. Next, the specialist team evaluates the corrective actions based on the criteria, using the same language variables (see Section 3.4.1).

- *Step 1.* Compute aggregate fuzzy ratings.

  The first step is to convert the linguistic weighting with the triangular fuzzy numbers.

Then, indicating with $w_g = (g = 1, 2, ..., c)$ the weights of the criteria (C_c) and $D_k = (k = 1, 2, ..., k)$ the ratings of each expert, the aggregate fuzzy weights $(\widetilde{w_{ij}})$ of each criterion are calculated as:

$$\widetilde{w}_{ig} = (w_{g1}, w_{g2}, w_{g3}) \tag{4.17}$$

where

$$w_{g1} = \min_k\{w_{g1k}\}, \quad w_{g2} = \frac{1}{k} \times \sum_{k=1}^{k} w_{g2k}, \quad w_{g3} = \max_k\{w_{g3k}\}. \tag{4.18}$$

The aggregated fuzzy ratings $(\widetilde{x}_{ijk})$ of corrective action $(A_i\ i = 1, 2, .., m)$ with respect to each criterion are given by:

$$\widetilde{x}_{ij} = (a_{ig}, b_{ig}, c_{ig}) \tag{4.19}$$

where

$$a_{ig} = \min_k\{a_{igk}\}, \quad b_{ig} = \frac{1}{k} \times \sum_{k=1}^{k} b_{igk}, \quad c_{ig} = \max_k\{c_{igk}\}. \tag{4.20}$$

- *Step 2.* Compute the fuzzy decision matrix.

  A decision matrix providing the rating of each alternative against each criterion is constructed. The decision matrix can be represented as by $\widetilde{A} = [a_{ig}]_{m\times c}$ for a decision problem involving i alternatives and g criteria.

  The vector $\widetilde{W} = (\widetilde{w}_1, \widetilde{w}_2, ..., \widetilde{w}_c)$ representing the weights of the decision criteria is then calculated.

- *Step 3.* Normalize the fuzzy decision matrix.

  To overcome the differences between the units, the fuzzy decision matrix is normalized. Normalization allows to bring the various criteria scales into a comparable scale which is between zero and one. A normalized decision matrix is computed by applying the following formula to each element of the decision matrix:

$$\widetilde{N} = [\widetilde{\eta}_{gi}]_{m\times c} \quad where \quad \widetilde{\eta}_{ig} = \left(\frac{a_{ig}}{\max_i c_{ig}}; \frac{b}{\max_i c_{ig}}; \frac{c_{ig}}{\max_i c_{ig}}\right) \tag{4.21}$$

- *Step 4.* Compute the weighted normalized matrix.

  The weighted normalized matrix for criteria is computed by multiplying the weights $(\widetilde{w}_{gi})$ of the evaluation criteria with the normalized fuzzy decision matrix normalization of the decision matrix ($\widetilde{\eta}_{ig}$).

$$\widetilde{V} = [\widetilde{\nu}_{ij}]_{m \times c} \quad where \quad \widetilde{\nu}_{ij} = \widetilde{\eta}_{ig} \times \widetilde{w}_{gi} \tag{4.22}$$

- *Step 5.* Compute the fuzzy positive ideal solution and fuzzy negative ideal solution.

  Using the elements of the weighted normalized decision matrix, the positive ideal (A^+) and negative ideal (A^-) solutions are determined as follows:

$$A^+ = (\widetilde{\nu}_1^+, \widetilde{\nu}_2^+, ..., \widetilde{\nu}_m^+) \quad where \quad \widetilde{\nu}_i^+ = \max_i(\widetilde{\nu}_{ig3}) \tag{4.23}$$

$$A^- = (\widetilde{\nu}_1^-, \widetilde{\nu}_2^-, ..., \widetilde{\nu}_m^-) \quad where \quad \widetilde{\nu}_i^- = \min_i(\widetilde{\nu}_{ig1}) \tag{4.24}$$

- *Step 6.* Compute the distance of each alternative.

  Euclidean distances of each alternative from the positive ideal solution and the negative ideal solution are calculated as follows:

$$d_i^+ = \sum_{i=1}^{m} d_v(\widetilde{\nu}_{ig}, \widetilde{\nu}_{ig}^+) \tag{4.25}$$

$$d_i^- = \sum_{i=1}^{m} d_v(\widetilde{\nu}_{ig}, \widetilde{\nu}_{ig}^-) \tag{4.26}$$

  where $d_v(\widetilde{a}, \widetilde{b})$ is the distance measurement between two fuzzy numbers $\widetilde{a}$ and $\widetilde{b}$.

- *Step 7.* Compute the closeness coefficient of each alternative.

  The closeness coefficient (Γ) represents the distances to the fuzzy positive ideal solution and the fuzzy negative ideal solution simultaneously. The closeness coefficient of each alternative is calculated by:

$$(\Gamma_i) = \frac{d_i^-}{d_i^- + d_i^+} \tag{4.27}$$

- *Step 8.* Rank the alternatives.

  In the last step, the different corrective actions are ranked based on the relative closeness values. The most appropriate corrective action has the highest Γ value. It is closest to the fuzzy positive ideal solution and farthest from the fuzzy negative ideal solution.

4.5 User Interface

The last component of the tool's framework is the User Interface (UI) that allows the visualization of the information and the user interaction. The UI makes all collected and processed data available, displays the information in a simple and intuitive way, and supports the decision-making process.

The tool is equipped with five main screens, each with different functionalities and accessible through the menu bar on the left. The main screen is the Dashboard where the most important information is briefly displayed. A support screen has been implemented for the configuration of the process virtual model and the other tool parameters (i.e., Settings). There are also screens for detail analysis of the data collected (i.e., Data) and processed (i.e., Report). Finally, a screen for the management of anomalies (i.e., Problem Manager) has been developed with the aim of supporting the decision-making process of energy efficiency improvement.

Dashboard

The Dashboard provides information on the energy efficiency of the production process. The screen shows all the information on the energy flow, the process status and the KPI trend, while the top bar contains display filters (Figure 4.8).

The screen displays the process energy efficiency mapping as defined in Section 3.3.2 with the opportunity of customizing it using the filters. They allow to modify the detail level of the visualization, the analysed product type and the indicators.

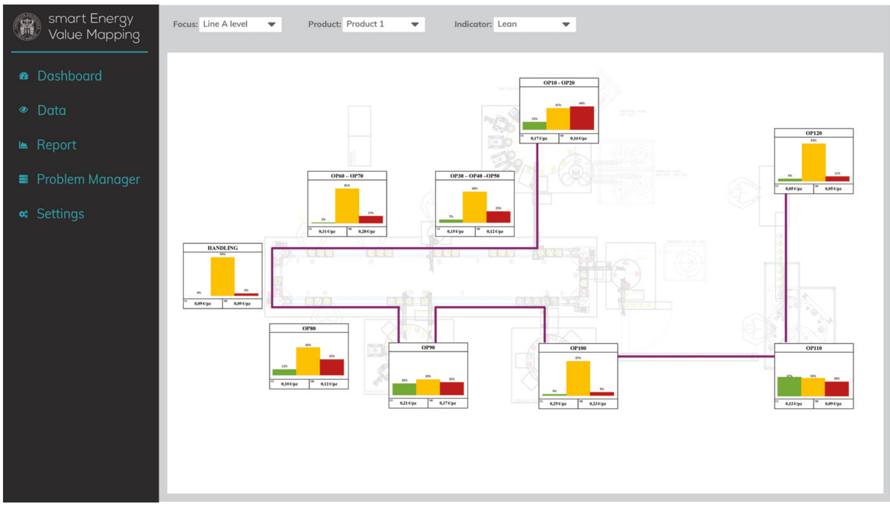


Figure 4.8: Dashboard - Detailed visualization and lean indicators

The hierarchical visualization displays energy data at different levels of detail, from the single machine tool and the production line to the whole factory plant. As an example, the Figure 4.8 shows the visualization of lean indicators applied to a production line for a single product, while the Figure 4.9 shows a visualization by departments with indicators related to energy consumption and maximum reference values.

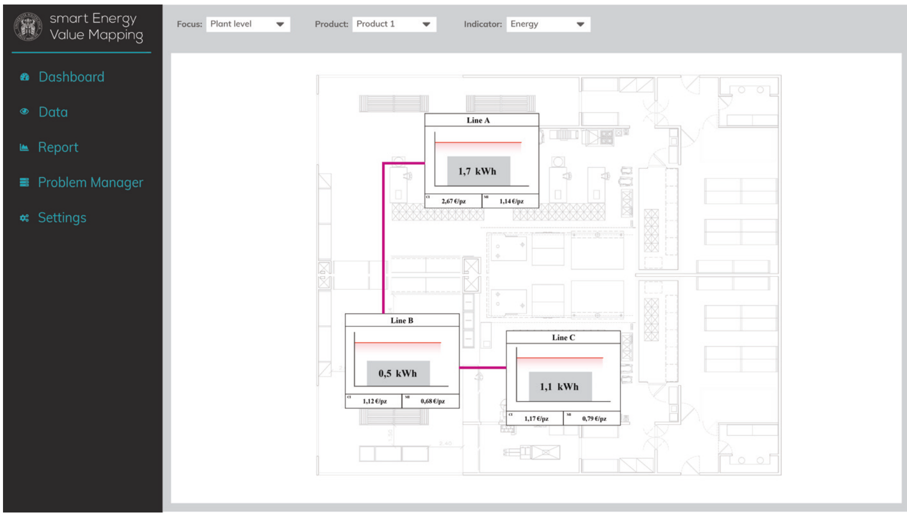


Figure 4.9: Dashboard - Plant visualization and energy consumption

The dashboard is continuously updated allowing to analyse the production process in real-time. The update time is set according to the production cycle time and the type of processes analysed.

The data is visualized through appropriate indexes that allow to identify the inefficiencies of the production process. The employment of performance indicators based on the lean methodology allows to easily identify the machines and the systems with high percentages of energy used for activities not related to VA. In the dashboard screen, the information is concentrated in the Process Box avoiding the information overload. The indicators are determined according to the type of production process and to the needs of the company. They can be established according to the working cycle time, the produced pieces, the working shifts or for specific time periods (e.g. working day, week, month and year).

Setting

The Setting screen allows to configure the different parameters of the tool.

A wizard procedure has been also implemented to support the definition of the virtual process model. At first access, the user sets up the structure of the production process defining all its features (e.g., equipment, relations, activities, etc.). The configuration is made through appropriate screens that guide the user in the creation of the structure. The compilation is carried out through a wizard procedure and combo boxes to avoid errors in the data structure. Figure 4.10 shows the screen for setting the characteristics of a machine (i.e., machine family and type, rating power, definition of the task performed and mode of operation).

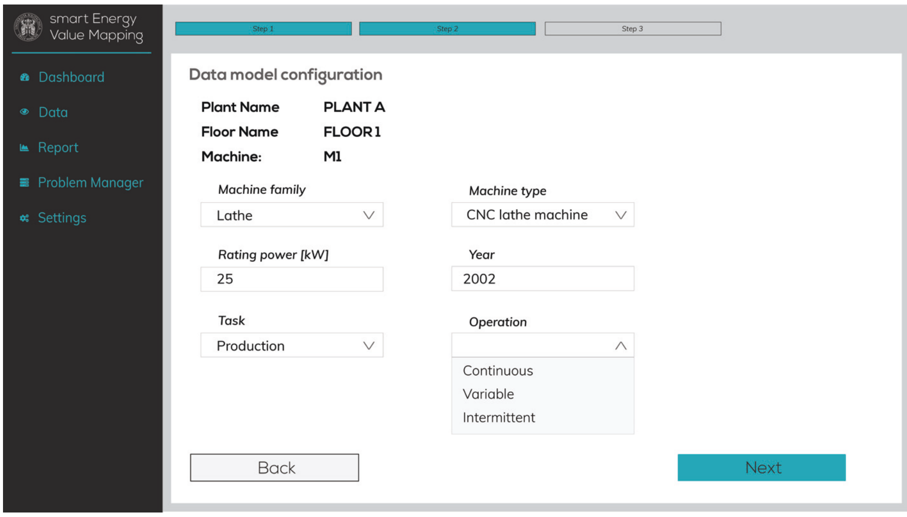


Figure 4.10: Setting - Data model configuration screen

Data

In addition to the synthetic information of the dashboard, the user can access and visualize the point data collected by the production process (Figure 4.11). The filters, placed in the upper part of the screen, allow to modify the type of variable and its visualization, and to perform analysis on different periods.

In detail, the filters allow to select the element of the process (e.g., single workstation, machine or entire process) and the period to be considered. They also allow to set the parameter to be displayed (e.g., active power, reactive power, apparent power, energy consumed, etc.), the type of visualization (i.e., line charts, pie charts, histograms and tables) and the time (e.g., trend, hour, day, etc.). Finally, it is possible to export the displayed data in .cvs format.

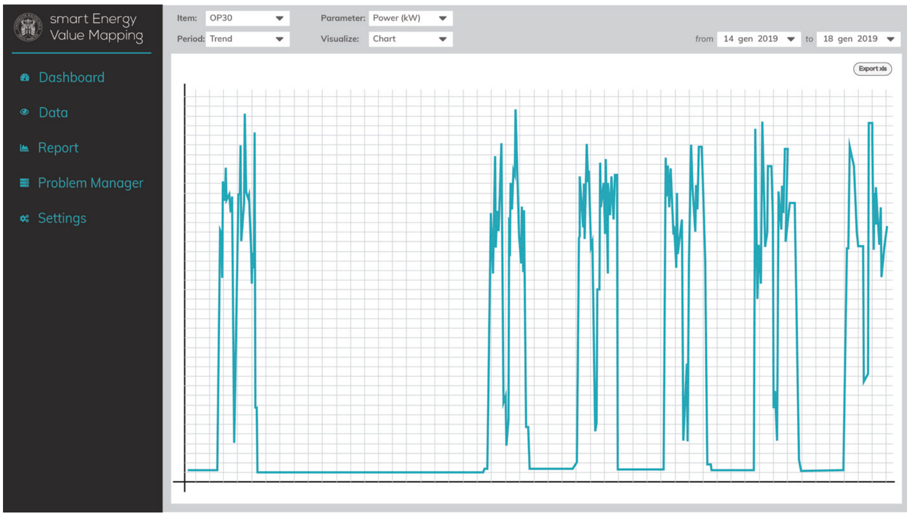


Figure 4.11: Data

Report

Beyond the Data screen, a screen to display the information elaborated by the tool has been implemented. The Report screen allows the visualization and analysis of the indicators relating to energy consumption, production and energy efficiency trends (Figure 4.12).

Also in this screen, there are filters to customize the visualization. They allow to select the process element, the time period and the indicator to be considered. The tool allows the graphical or tabular visualization. In the lower part of the screen, the average and reference statistical values are shown.

Problem manager

The Problem manager allows the user to manage the anomalies in the production process.

When the tool detects an anomaly, it issues different notifications depending on the way the alarm was set up. After opening the UI, the table with all problems is shown to the user, offering two possibilities to process the anomaly (Figure 4.13). The user can either cancel the problem by deleting the notification or choose the start problem-solving button. The latter button redirects the user to a problem-solving service.

Figure 4.12: Report

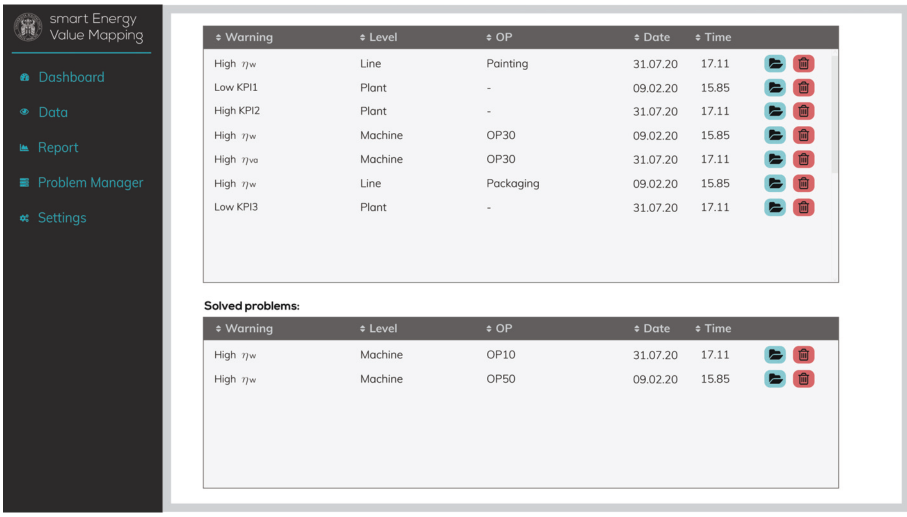


Figure 4.13: Problem manager

The problem-solving service screen allows the user to view all the information needed to understand the anomaly and the possible corrective actions (Figure 4.14). It is structured in five main sections:

- General data about the anomaly: ID, date and time.
- Alarm recipient: name of the process manager, plant manager and energy manager involved in the event.

- Anomaly features: name of the indicator with the data out of threshold which has generated the anomaly, machine/workstation involved and company level of the report.
- Probable cause for the anomaly: description of the reason that led to the energy inefficiency of the process.
- Potential corrective actions: description of the corrective measure identified by the tool using the algorithms defined in the Section 4.4.3.

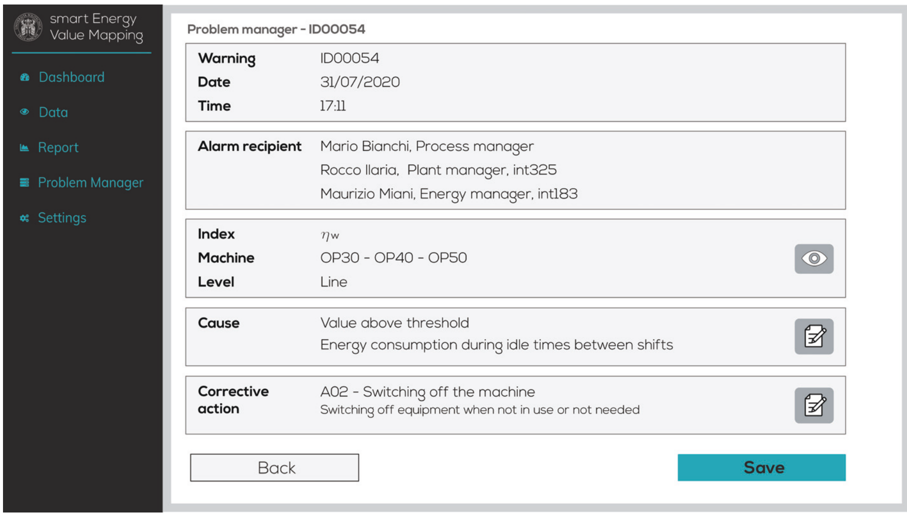


Figure 4.14: Problem manager - Problem-solving service screen

In addition to the main features, the screen contains buttons to increase the understanding about the anomaly and to edit data.

In detail, in the *features* section, a button has been included to allow the user to move to the Report screen. The direct link enables the visualization of the data relative to the time interval in which the problem was reported. This gives the user the opportunity to analyse all the data and increase awareness of the anomaly.

In the *causes* section, the button allows to launch a pop-up window for data modification. The user can modify the cause that originated the anomaly, selecting another one from the internal database or alternatively add a new one.

Also in the *corrective actions* section, the user has been given the possibility to edit data. By clicking on the edit button, a pop-up window opens in which the corrective actions identified by the tool are displayed. The user can modify the choice made by the tool, selecting another one or if not available, add a new corrective action (Figure 4.15).

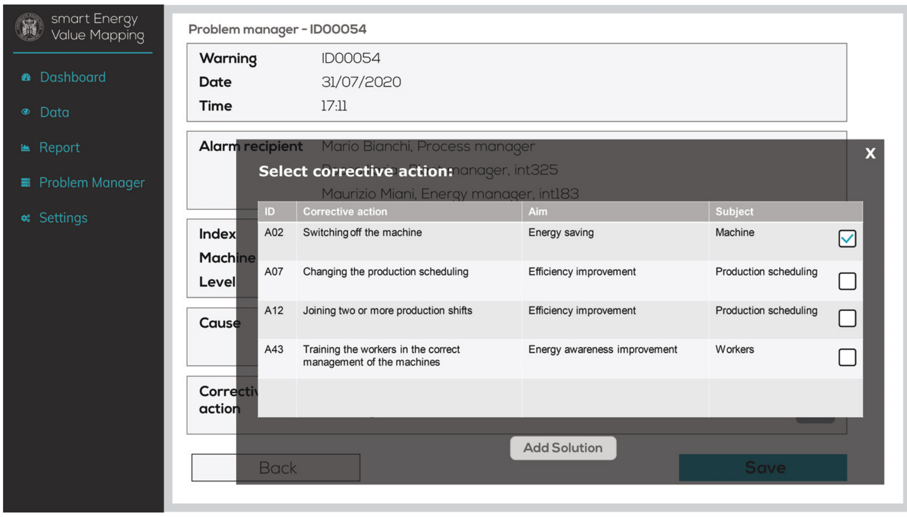


Figure 4.15: Problem manager - Corrective action edit screen

After the data analysis, the user can decide to intervene immediately on the anomaly or postpone the resolution.

In the former case, the user indicates to the tool the corrective action that has been chosen, confirming the data. The tool stores the user feedback and records it in the system repository. In a continuous learning process, the corrective actions are updated in relation to the anomalies identified. Finally, the tool moves the problem report to the solved problems.

If, on the other hand, the anomaly resolution is postponed, the user does not save the data and return to the main screen. The tool deletes the anomaly warning and leaves the problem report among those to be resolved.

Chapter 5

Validation

The smart Energy Value Mapping (sEVM) tool has been tested in the context of the manufacturing industry with the aim to improve energy efficiency. Two different use scenarios have been identified to show how it can adapt to different contexts and is able to support users in the reduction of inefficiencies.

The first scenario consists of a highly automated production line in which a single product is assembled. The second scenario, on the other hand, analyses a manufacturing plant with a high incidence of manual activities in which several batches of products are created.

The proposed tool has been provided to energy managers and process managers connected with the productive systems of the two case studies, to monitor efficiency and energy flows. The modelling of the production process within the tool has been carried out by the energy managers with the support of the other company managers. In detail, the plant managers have been consulted for the data collection related to the asset characteristics, while the lean managers have been engaged for the characterization of the activities. The analysis and recommendations of the tool have enabled the energy managers to identify and solve the main inefficiencies of production processes. In the definition and implementation of the action plan, operators and management staff have been also involved. The tool has been used by all stakeholders (i.e., workers, process managers and energy managers) to monitor and then evaluate the efficacy of the implemented corrective measures.

The case studies demonstrated the effectiveness of the tool in terms of energy efficiency, reduced costs and reduced environmental impact.

5.1 Case study I: Automatic production line

The first case study has been conducted in collaboration with an international company committed to the design and production of hi-tech systems and components for the automotive sector.

Its business areas are: automotive lighting, electronic systems (e.g., instrument clusters; infotainment and telematics), powertrain (e.g., engine control systems for gasoline, diesel and multifuel engines, hybrid electric systems and components, transmissions), suspension systems, exhaust systems (e.g., catalytic converters and silencing systems), motorsport (electronic and electromechanical systems specifically for championships at the cutting edge of technology, in F1, MotoGP, WorldSBK and the WRC), after-market parts and services. Through a process of constant innovation, the company develops new intelligent automotive systems and solutions that make it a supplier to all the leading car makers in Europe, North and South America, and Asia-Pacific region.

The company has always been focused on sustainability issues and in recent years is engaging in digital transformation in its plants using enabling technologies for Industry 4.0, analysis of the large amounts of data which are generated by systems, and support for workers' decision-making processes.

The Italian production plant located in Bari that produces powertrains was involved for the validation. In particular, engine and transmission components for cars, motorcycles and light vehicles are produced. Its product range focuses on engine control systems and transmission technologies. The company produces both hardware components, the electronic control units that pilot the engine, and their sophisticated software. The systems supplied to car manufacturers also include certain parts which are crucial for engine performance and emissions: injectors, air-gasoline and air-diesel manifolds, throttle bodies.

The plant covers about 300 thousand square meters, employs a thousand workers and has a turnover of about 200 million euro per year. It is organized into several areas, each one dedicated to a specific product. The lean philosophy and World Class Manufacturing methodology is deeply rooted in this plant, and customer value is one of the main drivers.

The Gasoline Direct Injection (GDI) pump department was chosen for the validation. The GDI technology is an advanced injection system for gasoline engines that, combined with turbocharger, allow engine downsizing, improved performances, and significant reductions in fuel consumption and emissions. The case study has allowed to evaluate how the tool supported operators in analyzing and managing the energy flows of a highly automated process.

5.1.1 Production process

The GDI pumps department is composed of an assembly line consisting of several automated workstations connected through a conveyor belt. The process assembles the various components and through several machining operations generates a high performance GDI pump (Figure 5.1). The main features are:

i) fuel pressure up to 500 bar, *ii)* flow control with electromagnetic actuator on inlet valve, *iii)* worldwide fuel compatibility (full stainless steel), *iv)* integrated relief valve, *v)* integrated variable feed pressure damper and *vi)* compact dimensions and reduced weight.

Figure 5.1: GDI pump

The process consists of twelve workstations, two manuals and ten fully automated (Figure 5.2). The process is composed as follows:

- OP 1.10: it is the first workstation where the plunger and the body are loaded. The task is performed by an operator while the equipment checks the coherence between the loaded components.
- OP 1.30: it is the workstation where the overpressure valve is assembled. The tasks are completed without human intervention and concern, first, the assembly of the pin, spring and sphere and, then, the seat press-in. After the spring load control, the machine performs the cap press-in and position control.
- OP 1.40: the workstation performs the assembly of the outlet valve with the hp fitting. In detail, the valve is positioned, and then, the outlet valve ball, spring, stopper are assembled. Stopper crimping and machining control is performed. Finally, the hp fitting is assembled, controlling torque angle.
- OP 1.50: the executed task consists in the installation of the inlet fitting. In detail, the inlet fitting is positioned and then, press-in and welded. Finally, the correct fitting welding execution is checked.
- OP 1.60: the workstation makes the assembly of the on/off valve. The first task is the installation of the inlet valve inside the pump body. Then, the ring nut is inserted, screwed and crimped. After load/stroke and torque/angle control, the needle is inserted and the on/off valve is welded. At the end of the station, the welding and needle stroke controls are installed indicating non-conforming products.
- OP 1.70: it puts the plunger and the sealing cup inside the pump body. In detail, a handling robot inserts the plunger into the body after checking

the coherence between body and plunger. Then it places the sealing cup under pressure and controls the load/stroke.

- OP 1.80: the workstation executes the sealing cup welding, puts the filter inside the pump body and controls the load/stroke.
- OP 1.90: the damper is assembled in this workstation. A robot takes the four components of the damper and puts together in the pump. After fixing them, it checks the load/stroke.
- OP 1.100: the workstation carries out two tasks: the first concerns the welding of the damper and the subsequent control of the welding correct execution. The second task is the welding the on/off valve coil.
- OP 1.110: it is responsible for the quality control and consists mainly of four stations. They conduct the pump tightness test in order to check for (Helium) leaks and non-conformities of the product.
- OP 1.120: the workstation assembles the last components of the pump. The first task is taking the half cone and positioning it in the pump and repeat the same operation with the spring. The second task is putting the spring retainer and checking the half cone position.
- OP 1.130: it is the last workstation of the production process in which the GDI pump is unloaded by the operator and loaded on container. In addition to unloading, the operator manually inserts the protection cap on the finished product.

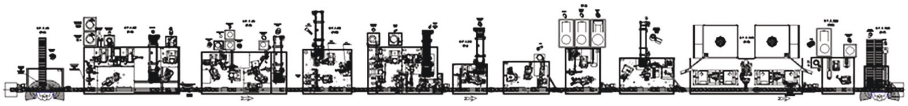


Figure 5.2: Layout of GDI pump assembly line

5.1.2 Data collection and analysis

Following the procedure model in Section 3.2, the steps data collection and data analysis are performed.

The first step concerns the creation of the process virtual model. The twelve workstations have been loaded into the tool together with the machines that compose them. After that, each machine is defined through its characteristics, relations and tasks. This allows to define the process data structure on which raw data are stored.

The tasks are then classified according to the lean methodology. Table 5.1 shows the process tasks classified as value-added (VA) and the non value-added (NVA) tasks supporting the process.

Table 5.1: Classification of process tasks

OP	VA	NVA
1.30	t1 · t2 · t7	t3 · t4 · t5 · t6 · t8 · t9 · t10 · t11
1.40	t1 · t2 · t5	t3 · t4 · t6 · t8 · t9 · t10
1.50	t2 · t3	t1 · t4 · t7 · t8 · t10
1.60	t1 · t2 · t3 · t4	t5 · t6 · t7 · t8 · t9 · t10
1.70	t1	t2 · t3 · t4 · t5 · t9 · t10
1.80	t1 · t2	t3 · t10
1.90	t1	t2 · t3 · t4 · t10
1.100	t1 · t3 · t4	t5 · t6 · t9 · t10
1.110	t1 · t2 · t3 · t4	t5 · t9 · t10
1.120	t1	t2 · t3 · t6 · t10

After characterizing the process and classifying the tasks, process data is collected.

The tool is installed in a specific server placed near the assembly process. The machine is connected to the sensors and to the process control system (i.e., PLC) through the company network infrastructure. It is also connected to the company's management systems (i.e., MES). The employment of the PLC-based monitoring system allows the capture of data and energy flows with a high sampling rate.

The collected data concern energy consumption, production process status, quality and maintenance. In detail, the data collected are related to: *(a)* the active power, *(b)* the variable of machine status to characterize the status of the process and *(c)* the cycle time to identify any anomalies in the production. Regarding the quality of the product, the pieces produced and rejected/reworked pieces are analysed. Such variables allow to calculate and analyse the process efficiency and to identify possible patterns of inefficiency. Finally, the maintenance data are collected in order to recognize production interruptions, the involved workstation and the fault cause.

The validation has run for 4 months in which the tool has monitored the process energy efficiency. It has also supported the decision-making process for the identification of the corrective action as a result of the detection of an anomaly. Off-line analyses are conducted on single work shifts since the process operates on three work shifts. In addition to the indicators defined by the method, two other indicators that are usually employed in the company have been analysed, that is, SEC and OEE.

5.1.3 Results

Collected data has allowed mapping the energy flow and determining the energy efficiency of the assembly line. The analysis of the average consumption of a work shift shows that the process has a consumption of 186.21 kWh with a cost of 29.24 €. In detail, the OP 1.110 is the most critical workstation: it requires more than half of the electricity consumed by the whole process. It has an energy consumption of 133.63 kWh, while the other workstations have low consumptions (i.e., OP 1.30 and OP 1.50 have an energy consumption of 8.67 kWh and 6.06 kWh, respectively). The energy consumption of the workstations is shown in Figure 5.3 .

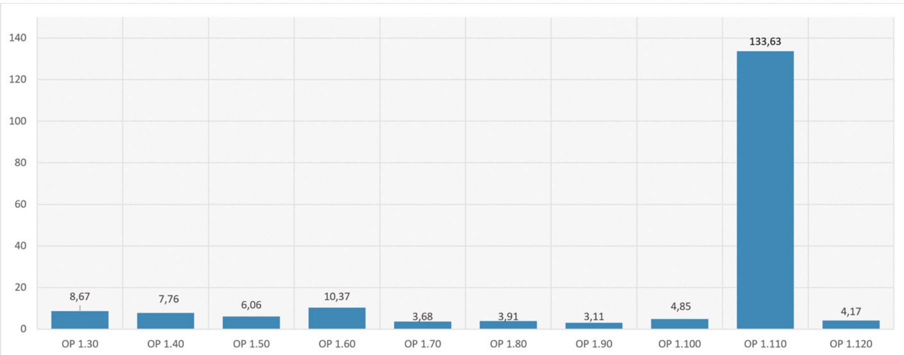


Figure 5.3: Energy consumption of workstations [kWh]

The various energy components and the indicators have been determined using the tool. The result is the map shown in Figure 5.4.

The process energy efficiency mapping reveals that the workstations with high percentages of W energy are OP 1.100, OP 1.40, OP 1.70 and OP 1.30, while high percentages of NVA energy are observed in OP 1.90, OP 1.80 and OP 1.70. The values of CI and MI highlight that OP 1.110 is the most critical workstation (i.e., 20.98 € and 10.07 € per work shift, respectively). Then there are the workstations OP 1.30, OP 1.40 and OP 1.100, but to a lesser extent. These workstations are the most energy intensive and those with the highest percentages of NVA and W energy.

Overall, the assembly process consumes 129.21 kWh (i.e., 69%) for VA activities, 11.24 kWh for NVA activities, and 45.77 kWh for W activities.

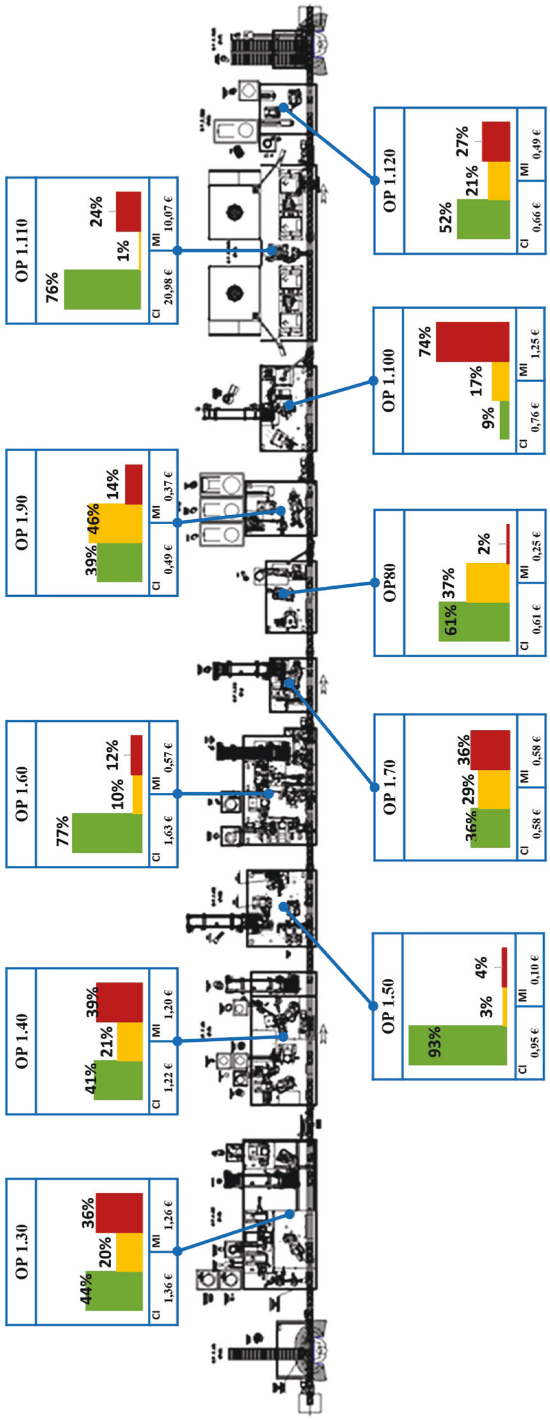


Figure 5.4: Energy value mapping of the assembly process

Then, the tool has allowed the identification of the anomalies in the machines management and the process energy inefficiencies.

Through the comparison of the indicator trend with the historical data, the tool has detected the inefficiencies in real time. In detail, the exceeding of the control limits has allowed to identify those anomalous events where there is a high consumption of NVA and W energy.

As an example, the trend of the MI (Figure 5.5) and its moving-range (Figure 5.6) detected after a production interruption due to an extraordinary maintenance intervention is reported. At some point, the values overcome the control limits and the event is notified. By analysing the data, the tool identifies the cause and informs the operator that the workstations located downstream of the intervention is consuming energy unnecessarily.

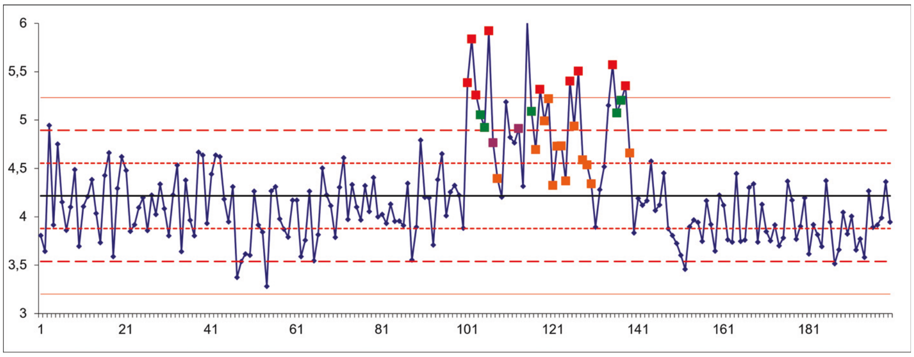


Figure 5.5: Trend of the MI with control limits

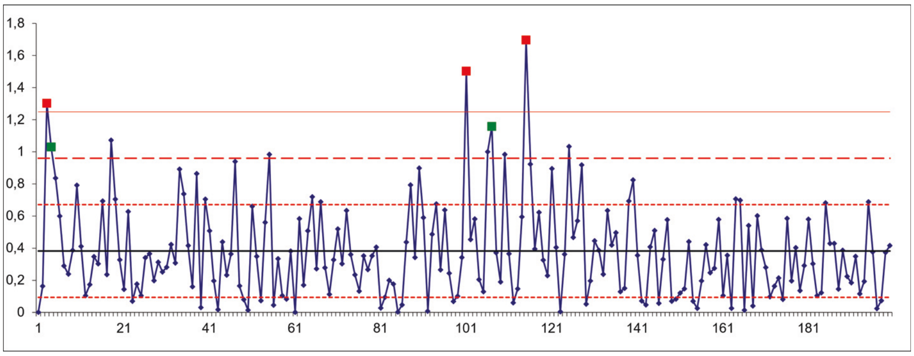


Figure 5.6: Trend of the moving-range related to the MI with control limits

Other production process anomalies are identified through off-line analysis. The components of NVA and W energy have been analysed in relation to the performed tasks (Figure 5.7). It has emerged that the NVA energy is mainly due to the tasks of workpiece handling (i.e., 50%) and the tasks of component positioning and preparation (i.e., 46%). On the other hand, the W energy is almost entirely due to the energy consumption during the idle time (i.e., 96%) in which the machines are waiting for the incoming workpiece.

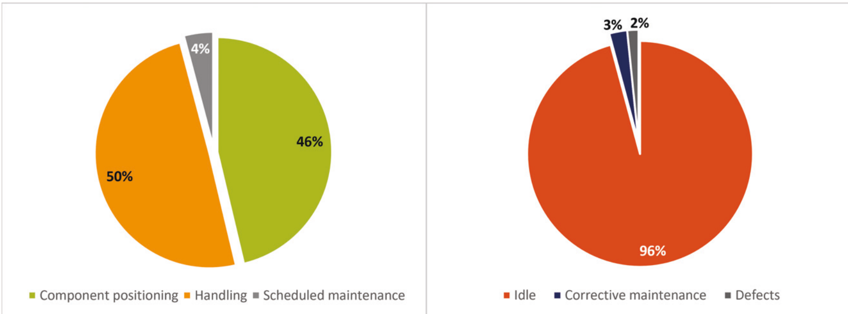


Figure 5.7: Breakdown of consumption of NVA energy (left) and W energy (right) by their tasks

After a 6-week period of production process monitoring, the tool has detected a total of 237 anomalies. For each of them, it has identified the responsible machine, the cause and has suggested corrective actions.

The main source of inefficiencies is related to the machine's energy consumption during idle times caused by the production interruptions due to lack of workpieces. The machines remain fully operational, although the production is stopped, absorbing about 24% of the total consumption. Looking at the single workstations, it emerges that the energy consumption during the idle times is a significant part of the energy consumption for not generating value (Figure 5.8). It is also uniformly distributed over almost all the workstations.

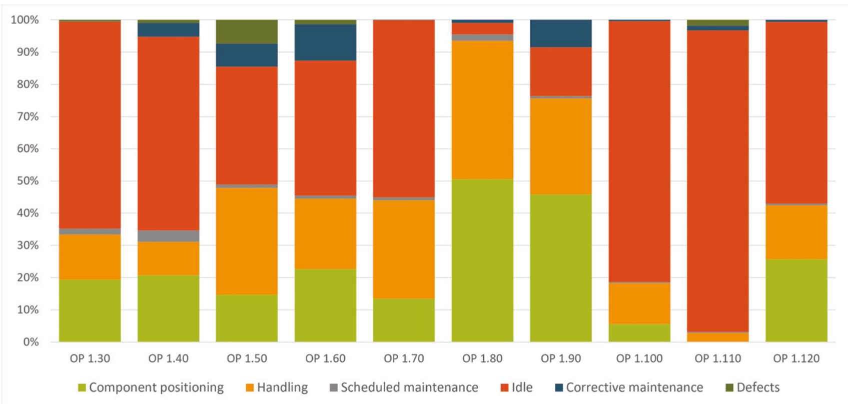


Figure 5.8: Breakdown of NVA and W energy consumption for each workstation by their tasks

Other anomalies have concerned the energy consumption during the extraordinary maintenance activities. The tool has detected energy inefficiencies related to production interruptions due to failures or breakdowns of some machines. In detail, the most frequent maintenance interventions have occurred at workstations OP 1.40, OP 1.50 and OP 1.60. These maintenance interventions are mainly related to punch breakage. In these workstations, after a variable number of cycles the punch becomes unusable and the load reaches a different position, deviating from the required specifications. This variation produces defective workpieces with a consequent increase in W energy. Then, the excessive increase of waste leads to production stoppage and requires an extraordinary maintenance intervention. The downstream workstations thus remain in waiting for the piece to be worked, increasing the W energy.

Finally, the tool has highlighted the outliers energy consumption of the workstation OP 1.120. Through the comparison with historical series, it has detected an increasing trend in energy consumption. The rising demand is due to components wear of the half-cone preparation and positioning system.

The energy manager together with the process manager have analysed the anomalies that have occurred most frequently during the monitoring period. Based on the data and the suggested corrective actions, they defined the action plan to improve the efficiency of the process.

The corrective actions described in Table 5.2 have been implemented.

Table 5.2: Action plan according to inefficiency causes

Corrective action	Cause	Where
Advanced machine on/off management during idle time	Stand-by mode during idle time	OP 1.30 OP 1.40 OP 1.100 OP 1.110
Predictive maintenance	Faulty components production and interruption of the productive flow	OP 1.40 OP 1.50 OP 1.60
Buffer installation	Stand-by mode during idle time	OP 1.110
Replace with energy efficient substitutes	Irregular energy consumption trend	OP 1.120

The corrective actions are mainly aimed at reducing the W energy due to the idle time of the workstations.

The first action concerns the implementation of a new machines management policy during idle time. Through the introduction of new control rules into the PLC, the equipment interrupts the energy consumption when the workpiece waiting time exceeds a threshold value. These control rules have been implemented in stations OP 1.30, OP 1.40, OP 1.100 and OP 1.110.

With the same aim, a buffer for the input of pieces for processing has been installed before the workstation OP 1.110. It allows to reabsorb little stand-by and small interruptions of the production process. This intervention has allowed to concentrate the production increasing the VA component, while in the remaining moments to turn off the machines, eliminating the W energy.

A new predictive maintenance policy has been implemented at workstations OP 1.40, OP 1.50 and OP 1.60. This measure allows to replace the punch before failure when one or more parameters exceed the threshold value. The corrective action optimizes the maintenance strategy by reducing unplanned downtime and increasing process uptime. Moreover, it allows reducing the number of produced defective parts.

Finally, the components of the workstation OP 1.120 have been replaced with new and more efficient components. The measure has reduced the inefficiency caused by the malfunctioning of the electric motor for the half-cone preparation and positioning system. It has concerned the replacement of the electric motor with a more energy efficient one.

After the action plan implementation, the process was monitored for 6 weeks. The result is the map shown in Figure 5.9.

The CI and MI indexes highlight that OP 1.110 remain the most critical workstation, even if the corrective actions allow to considerably reduce its energy consumptions. In detail, the energy consumed is reduced by 15%, bringing the CI to 17.63 €. The MI decreases from 10.07 to 3.37 €.

The process energy efficiency mapping shows a reduction of indicators at almost all workstations. This is attributed to the reduction of the W energy component.

Figure 5.10 shows the reduction of energy consumed during the idle times between the initial and current state. The highest reduction is at workstation OP 1.110 with about 20 kWh saved per shift, corresponding to an energy reduction of 64%. In the other workstations the reduction is an average of about 50%. The implemented action plan allows to reduce the energy consumed during idle times from 43.86 kWh to 15.83 kWh.

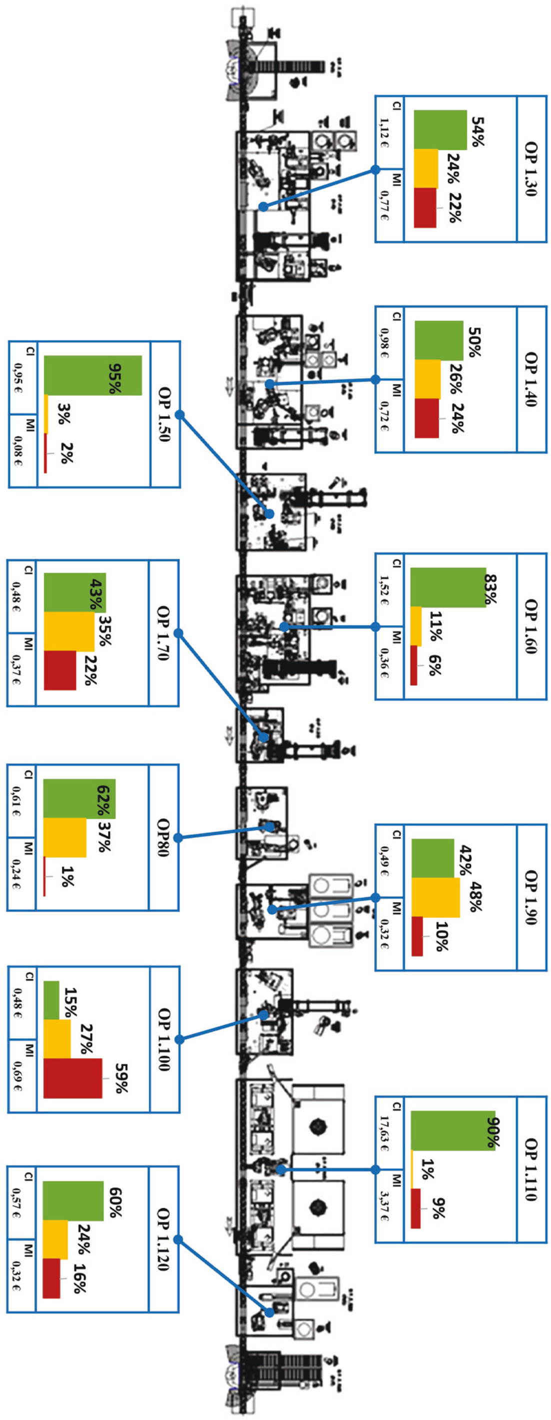


Figure 5.9: Energy value mapping of the assembly process after the action plan implementation

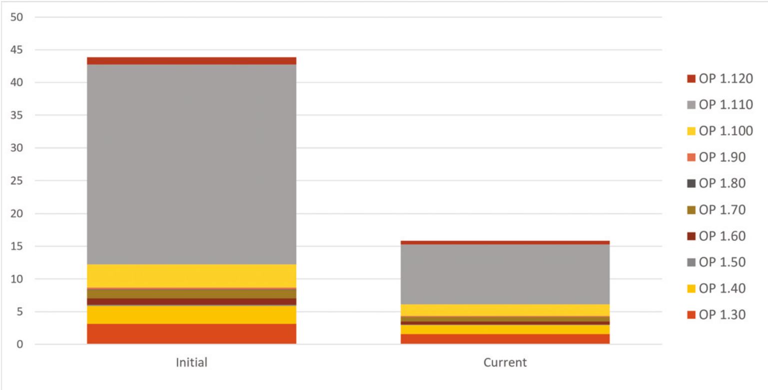


Figure 5.10: Comparison of the energy consumption [kWh] during idle times between the initial state and the current state

Overall, the assembly process has a consumption of 157.88 kWh with a cost of 24.79 €.

The comparison with the initial state highlights that the implemented action plan has led to an increase in energy efficiency (Figure 5.11). The reduction of NVA and W energy has allowed to increase the efficiency of 15% with the contextual reduction of the total energy consumed.

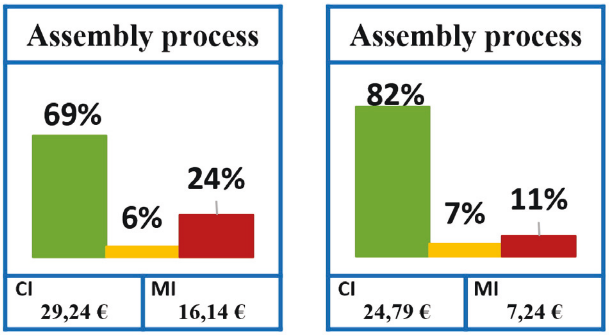


Figure 5.11: Comparison of the Process box between initial (left) and current state (right)

At the current state, the process consumes about 30 kWh less per work shift less than its initial state, saving 2668.90 € per year. The energy savings also reduce the company's carbon footprint. The reduction of kilowatt-hours has been converted into avoided units of carbon dioxide emissions using the national weighted average CO_2 emission rate related to Italy's energy mix (Footprint, 2019). The annual CO_2 saving derived from the implementation of corrective actions is 5615 kgCO_2e.

5.2 Case study II: Manufacturing plant

In the second case study the sEVM tool was tested in a whole manufacturing plant. The validation was carried out in collaboration with an Italian medium enterprise that produces high performance carbon fiber components for automotive industry.

The company core business is the design, prototyping and production of structural parts and components in advanced carbon fiber composite materials, both for the automotive sector (i.e., sports and GT cars, formula racing cars) and the motorcycle industry. It combines production with an intense research activity both on the product and on the process. In recent years, it is focusing on process control and other improvements based on the Industry 4.0 topics, with the aim of optimizing data management and increasing productivity. The company is also starting a research on the automation of several production phases with the use of man-robot cooperative systems.

The company production has a great variability: it ranges from the realization of a single prototype to a batch production in which the products are made as groups or small amounts. The company offers studied and designed solutions to meet customer requirements. As a consequence, the final product can range from a single component with complex shapes (e.g., halo protection system) to all the carbon fiber composite components of a competition car (e.g., chassis, monocoque, car body, rear wing, etc.) (Figure 5.12). The high production flexibility allows the company to guarantee high quality standards.

Figure 5.12: Examples of company production

The experimentation has been carried out in the plant of Controguerra (TE) which has a surface of about 3000 square meters. The plant covers all the stages of manufacturing process. The case study allowed to examine how the tool works in the analysis of a whole plant and in a process with a high incidence of manual tasks.

5.2.1 Production process

The production process is organized in several stages in which the carbon fiber is processed to obtain components characterized by lightness and strength.

The process consists in the moulding of pre-impregnated reinforced material containing a thermoset resin. The pre-impregnated sheets are semi-finished products composed of fibers and resin in the liquid state which will then be polymerized. Pre-impregnated materials must be stored at low temperatures to avoid unwanted resin cure. The use of such sheets allows to have a good workability and to obtain products with high mechanical performance.

The process for bag molding consists in applying a certain pressure and temperature on the composite during the polymerization phase (through an autoclave). This result is achieved by using a flexible diaphragm, the bag, and using air to apply pressure.

The main steps of the process are:

- Cutting: in this phase the raw material is taken from a refrigerator where it is stored at a temperature below -18°C to preserve its chemical-physical characteristics. Then, it is laid on the cutting table to be cut in templates of desired shape, size, and orientation. The layers are finally removed, identified and stored.

- Stratification: it consists of manually depositing one or more layers of composite material on the mold. During the stratification it is necessary to carefully deposit the layers following precise procedures. It begins by applying a release film on the inner surface of the mould in order to facilitate the extraction of the piece after the polymerization. Sometimes hot air is blown to make the pre-impregnated sheets more foldable and adhesive. All these operations are repeated for each layer until the stratification is completed.
  In some cases, metal parts are added to allow the mechanical machining of the piece without affecting the structural characteristics of the composite material and, in the case of threads, perforated aluminium inserts are added to increase the mechanical resistance.
  After the deposition of each pre-impregnated sheets ply, the entrapped air between layers is removed by means of a preliminary debulking operation. Once the designed stacking sequence is reached, the vacuum bag is

created. The mold is covered by a nylon membrane, while the component is sealed with butyl rubber strips.

- Bagging: after the stratification phase, the component is bagged. It (i.e., procedure, method and materials) depends on the type of deposition, on the resin, on the thickness of the piece, on the pressure and temperature of the polymerization. Usually a release film and synthetic fabric are applied to facilitate the removal of the bag and the finished product. It is a phase that needs to be performed correctly, as it may cause the rejection of the part. The set of layers is covered by a bag and sealed. Then the vacuum is applied until the mold is placed in an autoclave. For larger thicknesses, several vacuum steps are used to eliminate air and secondary volatile products.

- Polymerization: after lamination and bagging, the entire assembly is placed inside an autoclave for curing and consolidation (curing phase). This process is reached out through the combination of external pressure, vacuum, and heat. The vacuum has the aim to eliminate air and volatiles while the external pressure to consolidate the laminate. The heat increases the velocity of the polymerization reaction until the complete cure of the matrix. The curing temperature and the pressure are maintained for 2 h or more, as function of the kind of resin and laminate, until the desired curing level is achieved. In some cases, a post-cure cycle is possible to allow the piece to achieve structural requirements and to reduce deformations.

- Finishing: at the end of the polymerization phase, the product is extracted from the mould and moved to the finishing phase. With the help of various tools, burrs and sharp edges are removed. If the final product is particularly complex, several pieces can be glued by applying bonding resins and the relevant catalysts using traditional techniques. The finished product is then sent to the quality control phase (for the final inspection) and its subsequent packaging for shipment to customers.

- Mechanical processing: if required by product specification, a high-precision mechanical processing is performed on the components, before quality control. The manufacturing process involves the milling of the component to remove burrs or other defects and drilling for final assembly. The working is performed by 5-axis numerical control (CNC) machines.

The production process is carried out in a shop floor organized in various departments that work independently (Figure 5.13).

According to the steps of manufacturing process, the departments are:

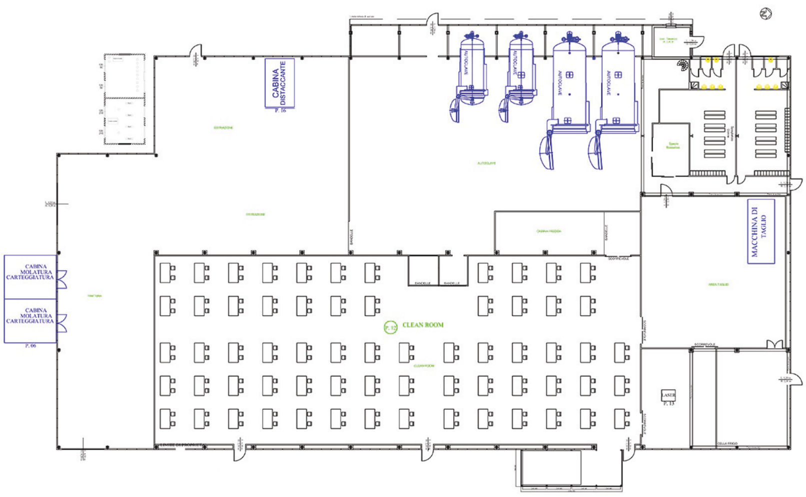


Figure 5.13: Layout of manufacturing plant

- Cutting: in this section the mechanical cutting of composite material sheets and the wrapping in production kits is carried out. The cutting operations are carried out in a temperature controlled chamber with air filtration. The processing is carried out with the use of a numerical control cutting machine. The machine is equipped with an aspiration bench that allows the scraps to be removed and collected in bags for subsequent handling as waste.

- Clean Room: the stratification process is carried out in a dedicated chamber called clean room. It has controlled temperature and humidity and an air filtering system to protect the workers and to prevent the deposition of external agents on the resin. The department is equipped only with small tools for the stratification of the raw material.

- Autoclave: it includes the bagging and the subsequent polymerization phase as they are closely related. It consists of four autoclaves and the dedicated auxiliary equipment (i.e., vacuum pumps, dryers and compressors). The autoclave is a large container pressurized with air and/or other gases and it is thermally insulated. The heating is provided by electric heaters. It has a considerable thermal source to provide rapid temperature variations, a pressurization system and an adequate system to keep the vacuum on the pieces before polymerization and during cooling after polymerization.

- Finishing: in this department, the workers, with the help of abrasive paper and/or mechanical equipment (e.g., grinder), carry out the latest processes on the component. The burrs and sharp edges are removed and the other finishing operations are carried out. The department is equipped with ovens, vacuum systems and other tools for manual tasks.

- CNC Machines: it includes two 5-axis numerical control machines and some manual workstations for mechanical processing. The machines include the auxiliary systems and are equipped with an extraction and filtration system that captures the dust and the processing scraps and stores them in specific containers.

5.2.2 Data collection and analysis

The implementation of the sEVM tool has started with the creation of the process virtual model. Through the support of the tool and its databases, the user has loaded the five departments that compose the plant. For each department, the machines which are involved in the process have been inserted with their characteristics, relations and tasks.

In order to make the analysis more accurate, the process virtual model has been completed with the technical equipment of the plant which are supporting the manufacturing process. They have been clustered as a single department called *Technical equipment*. It includes the compressed air system and the HVAC system.

Then, all activities of the departments have been identified and classified in order to properly allocate the energy consumptions. For this aim, the company's database, containing all internal reports compiled by operators, has been consulted. Each report describes when, where and why an activity is performed. In Table 5.3, the classification of departments activities is reported. NVA activities mainly include material handling, setting and maintenance, while W activities mainly refer to avoidable stops, breakdowns and defects.

After characterizing the process and classifying the activities, process data is collected.

The tool has been installed in the company server where all software are located. Subsequently, it has been connected with the company Manufacturing Execution System that allows to monitor the production progress, the traceability and the raw material flow. The tool has been also connected to the process sensors and to the principal machines involved.

Considering that the process is characterized by many manual operations and by a high average cycle time, a sampling time of one minute has been set for all departments.

Table 5.3: Classification of departments activities

	VA	NVA	W
Cutting	Cutting of compliant components Material load/unload	Set-up Regulations	Pause Defect - Raw material Defect - Semi-finished Failure Supply-related problems
Clean Room	Material layer laying	Components transfer	Pause Defect - Semi-finished Scheduled breaks
Autoclave	Curing and cooling Vacuum bag inserting	Set-up Material load/unload Regulations Scheduled maintenance interventions	Defect - Semi-finished Pause Failure Scheduled breaks
Finishing	Finishing processing Parts gluing and assembling	Components transfer	Defect - Semi-finished Scheduled breaks Pause
CNC Machines	Mechanical processing	Set-up Regulations Parts load/unload Scheduled maintenance interventions	Defect - Semi-finished Pause Failure Scheduled breaks
Technical Equipment	–	Production process supporting	Pause Failure Scheduled maintenance interventions

The collected data concern energy consumption, production process status, quality and maintenance. In detail, the data collected are related to:

- Active power;
- Process status to characterize the operation and the task performed by the equipment, and to calculate the process efficiency;
- Production time to characterize the net Operating time;
- Pieces produced and rejected/reworked pieces to monitor the product quality and to identify possible patterns of inefficiency;
- Maintenance data (i.e., failure, machine involved, intervention time and duration) to recognize production interruptions.

The tool has been used by the energy manager and the process manager to monitor the process energy efficiency over a 4-month period. It has also supported the decision-making process for the identification of the corrective action as a result of the detection of an anomaly.

Analyses are conducted on the work week, since each department operates with different work shifts and time schedules. The Autoclave operates on three work shifts, the Clean room on a single work shift with lunch break whereas the Cutting, Finishing and CNC machines departments work on two daily shifts.

Two more indicators usually used in the company (i.e., EE and OEE) have been analysed in addition to the indicators defined by the method.

5.2.3 Results

The tool has has allowed to determine the energy flow within the production process.

The analysis of the average weekly energy consumption has shown that the process uses 10297 kWh, with an average weekly cost of 1750.51 €. The most energy consuming department is the Autoclave with a consumption 6145 kWh which is about 60% of the total consumption and then, the Finishing and Technical equipment with 1343 kWh (i.e., 13%) and 1834 kWh (i.e., 18%) respectively (Figure 5.14).

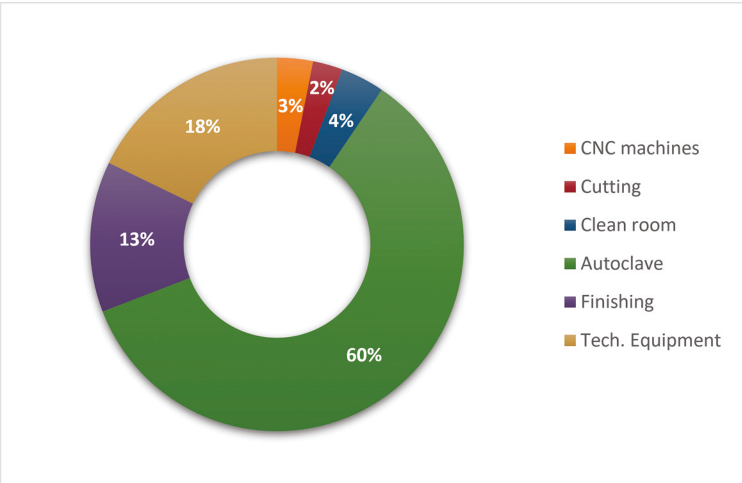


Figure 5.14: Distribution of total energy consumption by departments

Through the collected data, the tool has determined the energy efficiency of the manufacturing process. All the indicators included in the process boxes related to the departments have been calculated and the result is the map shown in Figure 5.15.

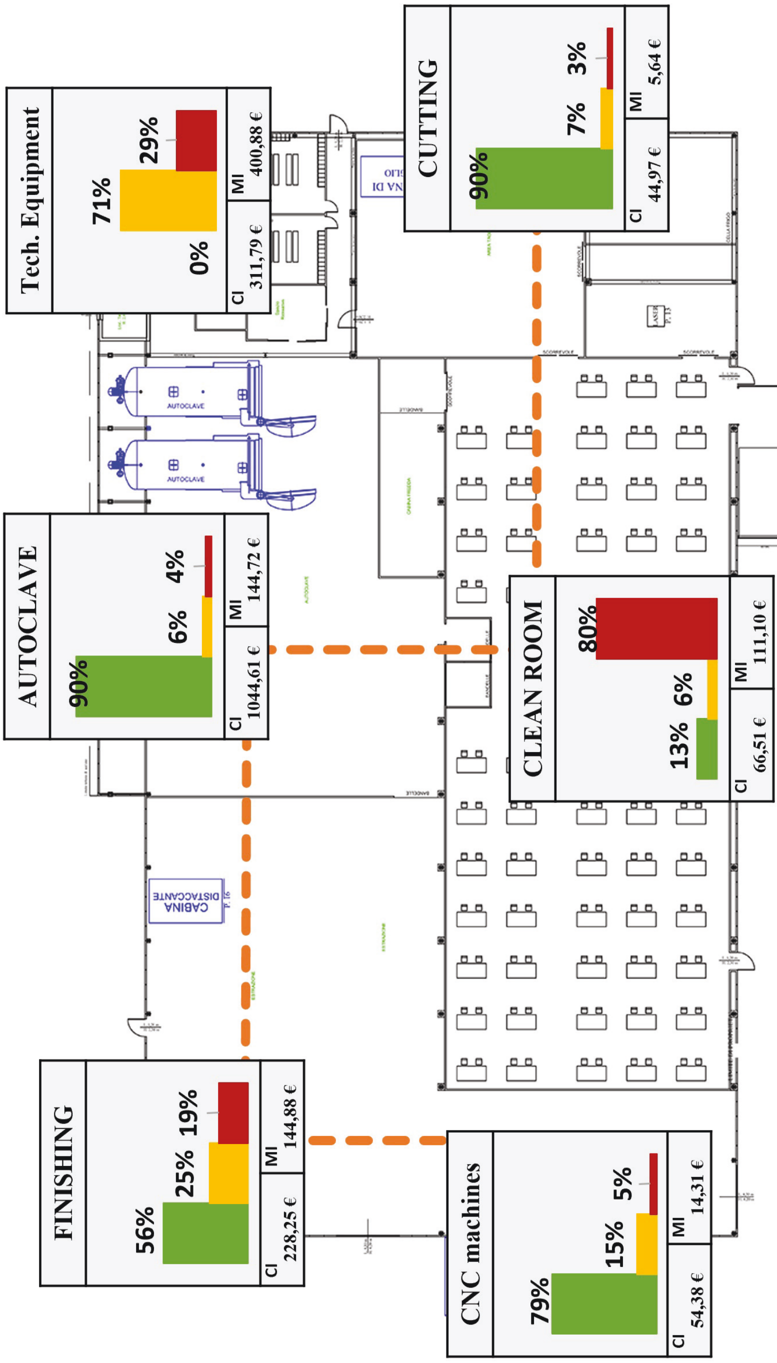


Figure 5.15: Energy value mapping of the manufacturing process

The process energy efficiency mapping reveals that the departments with high percentages of W energy are Clean room and Finishing, while high percentages of NVA energy are observed in Finishing and CNC machines departments. A separate discussion deserve the Technical equipment department that carries out only support activities to the process. It has no VA energy and the energy consumption is divided into NVA and W energy. In detail, it uses about of 1310 kWh for NVA energy and 524 kWh for W energy on average.

Notwithstanding the high CI value, the Autoclave department is not the most critical. The highest value of MI is found in the Technical equipment (i.e., 400.88 €). Then there are the Finishing and Autoclave departments with 144.88 € and 144.72 € respectively. Next is the Clean room department with 110.10 € and finally the CNC machine and Cutting departments with 14.31 € and 5.64 € respectively.

Overall, the manufacturing process consumes 6840 kWh (i.e., 66%) for VA activities, 2082 kWh (i.e., 20%) for NVA activities, and 1375 kWh (i.e., 14%) for W activities. Regarding NVA energy, 63% of it is absorbed by the Technical equipment, 17% by the Autoclave, and 16% by the Finishing department (Figure 5.16).

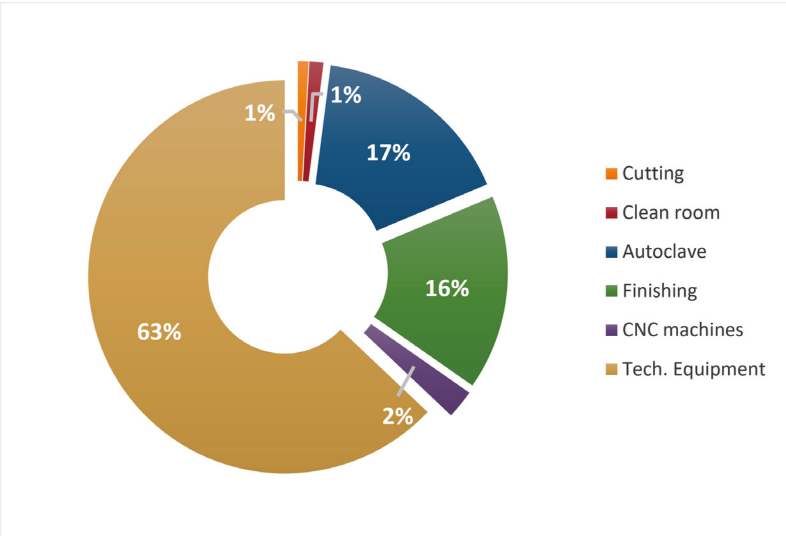


Figure 5.16: Breakdown of total NVA energy consumption for each department

Concerning W energy, the energy consumption distribution is more balanced except for the Cutting and CNC machines departments which represent 1% each (Figure 5.17). In detail, Clean room accounts for 23% of overall W energy consumption, Autoclave 18%, Finishing 19% and Technical equipment 38%.

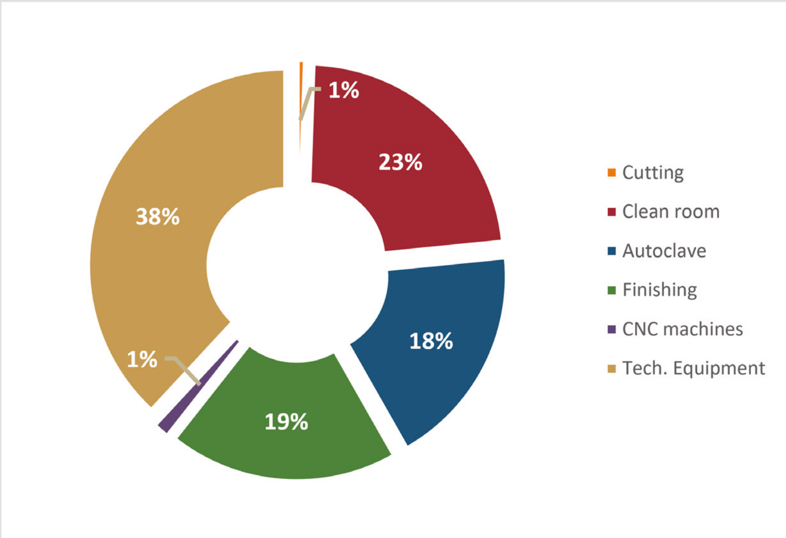


Figure 5.17: Breakdown of total W energy consumption for each department

The tool has allowed the identification of the process energy inefficiencies. They are detected through real time and off-line analyses. In the former case, the analyses are carried out through real-time comparison of the indicators' trend with the historical data. In detail, the exceeding of the control limits allows to identify those anomalous events where there is a high consumption of NVA and W energy. In the second case, the analyses examine the indicators and other process data in defined time intervals (i.e., working week).

Then, the components of NVA and W energy have been analysed in relation to the performed activities. It has emerged that the NVA energy is mainly due to the consumption of the departments' auxiliary facilities while scheduled maintenance has a very small impact on the total consumption. The auxiliary facilities represent the 90% of the total NVA energy consumption on average. They include department-specific equipment such as:

- cold chamber for raw material storage in the Cutting department;
- handling and lifting systems in the Autoclave department;
- dedicated compressors in the Finishing department;
- air treatment systems in the CNC machine department;
- lighting.

On the other hand, the W energy is almost entirely due to the energy consumption during the idle time in which machines are left on. Energy consumption during corrective maintenance interventions accounts for 4% while the defects and reworking for 12% of the total W energy consumption.

After a 6-week period of production process monitoring, the tool has detected a total of 78 anomalies. For each of them, it has identified the responsible machine, the cause and has suggested corrective actions.

The main source of inefficiencies is related to the machine's energy consumption during idle times between shifts. Looking at the single departments, it emerges that the energy consumption during the idle times is a significant part of the energy consumption for not generating value (Figure 5.18). In the Clean room department, it accounts for about 90% of all NVA and W energy consumption. In the other departments, the energy consumption during idle times is 26% on average.

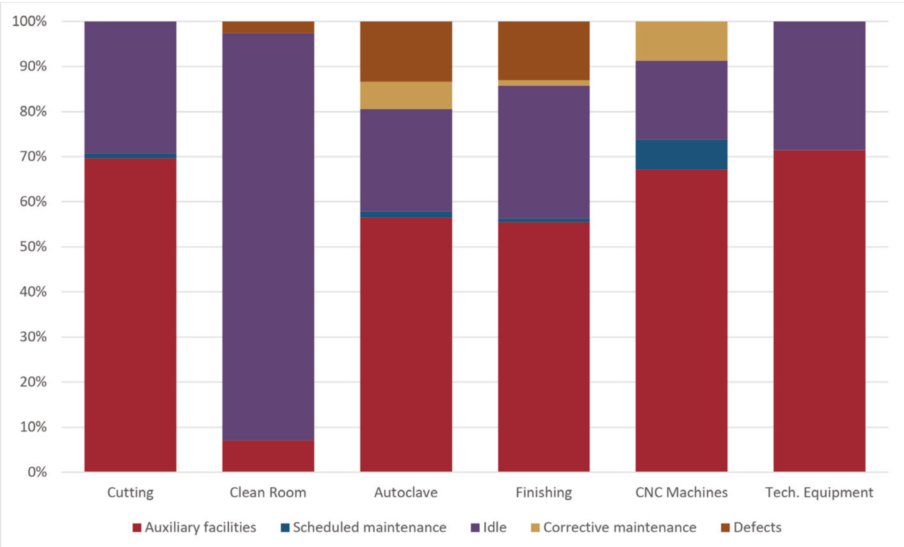


Figure 5.18: Breakdown of NVA and W energy consumption for each department by their activities

The tool has also highlighted when machines are left on, but no one is working on them, such as the extractor hoods in the Finishing department. Likewise, it has detected the continuous functioning of the HVAC system that maintains a fixed temperature in the Clean room and Cutting departments (i.e., 20°C) even if production has stopped.

Other anomalies have concerned the low energy efficiency of the autoclave. The tool has detected energy inefficiencies linked to the working cycles which are characterized by energy consumption per piece much higher than the average.

Finally, the tool has identified some energy anomalies associated with the compressed air system. The energy consumption of the compressors is always high even if the production is completely off.

The energy manager together with the process manager have analysed the anomalies that have occurred most frequently during the monitoring period. Based on the data and the suggested corrective actions, they defined the action plan to improve the efficiency of the process.

Table 5.4 summarizes the main causes of inefficiency and the specific identified corrective actions that allow improving the efficiency of the manufacturing process.

Table 5.4: Action plan according to inefficiency causes

Corrective action	Cause	Where
Improved machine on/off management during idle time	Stand-by mode during idle time	Cutting Clean room Autoclave Finishing CNC machines
Re-design of carts	Low energy efficiency	Autoclave
Install motion sensors	Stand-by mode during idle time	Finishing
Improved HVAC management	Stand-by mode during idle time	Tech. equipment
Reduce the operating pressure	Use of excessive air pressure	Tech. equipment
Section of compressed air circuit	Air losses due to the length and complexity of the distribution lines	Tech. equipment

The corrective actions are mainly aimed at reducing the W energy due to the idle time.

The first action concerns the improvement of the machine management policy during idle time. The correction measure provides for switching off machines during breaks or downtime, and when not needed for safety or other operational reasons. The implementation of switching off during idle times does not require any economic investment, but only a correct management of available equipment.

The equipments have been classified according to their function and divided into essential for the functioning of the production process (e.g., cold chamber for raw material storage) or not necessary. According to this classification, they have been divided also from the electrical point of view by separate control panels. Thus, the unnecessary equipments are switched off at the end of the work shift by the process manager, reducing W energy. The corrective measure has concerned all the plant's production departments.

The corrective action has also involved the machines left on during the work shift which do not perform any tasks. In this case, motion sensors have been installed so as to switch the machine off automatically after the operator has completed the task and moved away from it. The corrective measure has especially concerned the extractor hoods of the workbenches in the Finishing department.

Finally, the management program has been modified to optimize the functioning of the HVAC system when production is stopped. In detail, new logics have been introduced that allow to regulate the internal temperature according to the working shifts. The new programme have been applied to the Clean room and Cutting departments that need a constant working temperature. Instead, during the periods of inactivity of the departments, the temperature is controlled in a flexible way in order to reduce the energy consumed.

As far as the Autoclave department is concerned, new carts have been redesigned for loading workpieces. The new carts allow to increase the number of pieces that can be worked, increasing energy efficiency and productivity.

Regarding the compressed air system in the Technical equipment department, the corrective measure consists in reducing the operating pressure. The operating pressure is currently 6 bar, however, from the analysis of the technical characteristics, all the available equipment can work at a minimum pressure of 5 bar. The intervention is to reduce the operating pressure from 6 bars to 5 bars, and so decreasing the NVA and W energy components.

Moreover, the monitoring of the EE indicator has allowed analysing the electric energy consumed by compressors and detecting outlier consumption during the nights and non-working days. A more detailed analysis has showed that the anomalous consumption was generated by air losses due to the distribution lines layout. The intervention consists in the sectioning of the compressed air system, so as to reduce the dispersion generated by the departments that are not working.

After the action plan implementation, the process was monitored for 6 weeks and the result is the map shown in Figure 5.19.

The process energy efficiency mapping shows a reduction of indicators in all departments of the plant. The Autoclave department remains the department with the highest CI value even if it reduces the overall energy consumption by 17%. Analysing the energy efficiency, the Technical equipment department remains with the highest MI value even if it decreases by about 50%.

The W energy is reduced in all departments while increasing VA and NVA energy. In the Clean room department, the W energy is reduced from 80% to 25% of total energy consumed.

Figure 5.20 shows the reduction of energy consumed between the initial and current state. The implemented action plan has reduced the energy consumed by 22%.

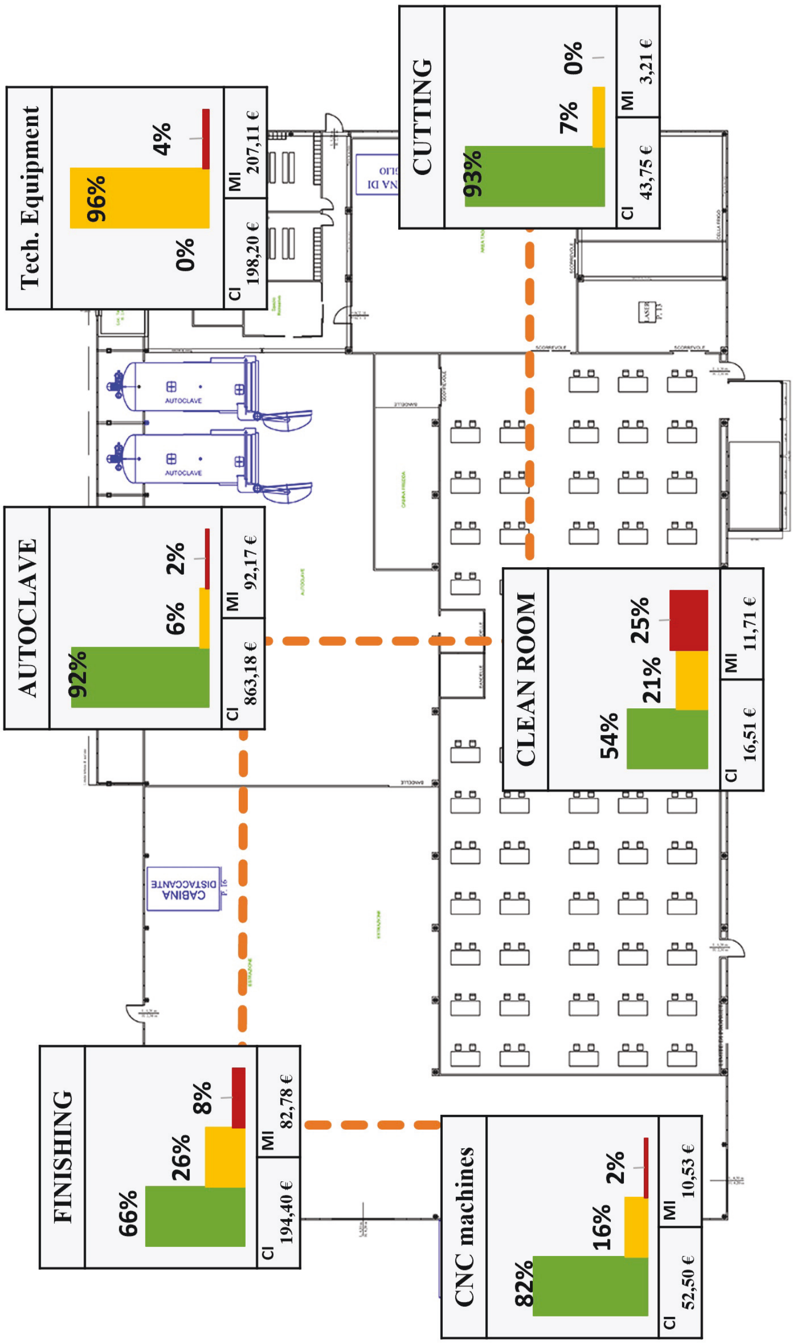


Figure 5.19: Energy value mapping of the manufacturing process after the action plan implementation

Analysing the different departments it emerges that the highest reduction has been seen in the Clean Room department with a 75% decrease in energy consumption. In the Autoclave department the reduction is 17% while in the Finishing department is 15%. In the Cutting and CNC machines departments the reduction is much smaller, and in the Technical equipment department the reduction is 36%.

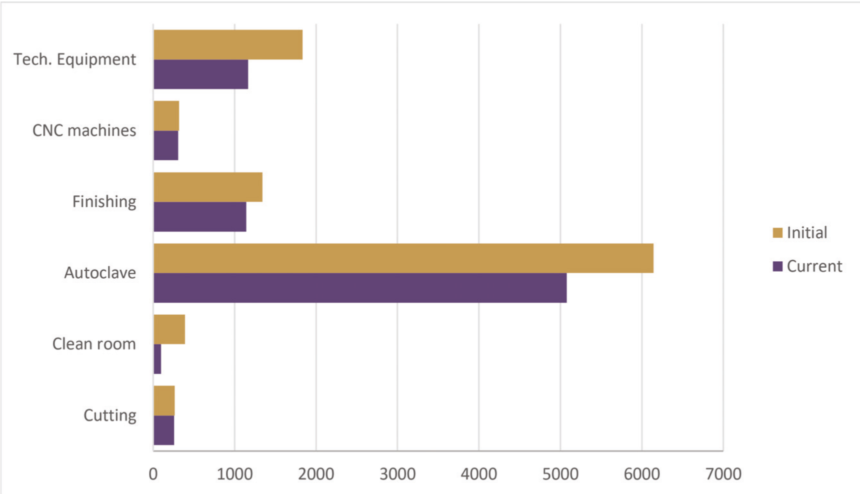


Figure 5.20: Comparison of the energy consumption [kWh] between the initial state and the current state by departments

Overall, the manufacturing process has a consumption of 8050 kWh with a cost of 1368.54 €. The comparison with the initial state highlights that the implemented action plan has led to an increase in energy efficiency (Figure 5.21). The reduction of NVA and W energy has allowed to increase the efficiency of 22% with the contextual reduction of the total energy consumed.

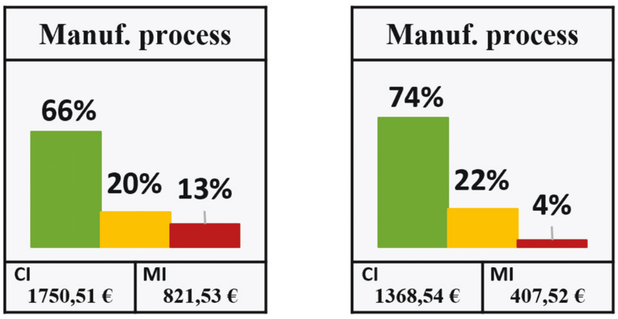


Figure 5.21: Comparison of the Process box between initial (left) and current state (right)

At the current state, the process consumes about 2247 kWh less per work week less than its initial state, saving 19862.26 € per year.

The economic saving is also associated with the reduction of environmental impact due to a lower energy demand to the electricity grid. According to the Italian energy mix, the reduction of CO_2 emissions corresponds to 735 kgCO_2e per work week (Footprint, 2019). In one year, the CO_2 saving is 38206 kgCO_2e, which is equivalent to the carbon sequestered by approximately 7000 trees of medium growth coniferous or deciduous tree planted in an urban setting and allowed to grow for 10 years (McPherson et al., 2016).

5.3 Discussion

Within the scope of the validation, the developed sEVM tool is examined regarding its relevance and usefulness. The application in two different case studies allows to validate the methodical approach and the tool against the research gap. This demonstrates that the tool (and also the method) fulfils the requirements of stakeholders in the energy management.

The tool provides diagnostics support of the production process by identifying the energy flows and problems in energy use. Information provided by energy consumption measurement systems and production management systems is collected. By monitoring production data and energy use parameters, the energy efficiency problems are identified. Finally, through real time and off-line analysis it identifies the cause and then, the most appropriate corrective action to reduce the inefficiency.

The graphical interfaces support the user in both the implementation and use of the tool. It supports the generation of the virtual process model with the description of equipment, process features and relationships. It also supports decision making process for manufacturing system improvement. The implemented prototype contains a knowledge base of about 180 energy efficiency measures. When an anomaly is detected, the tool creates a list of the most appropriate measures on which the user selects the most suitable one.

The two case studies have highlighted how the tool supports the energy manager and all stakeholders in the process energy efficiency assessment. In the first case study, the energy consumption of a production line has been analysed and the main inefficiencies and parameters affecting them have been identified. In the second case, the focus has been placed on an whole manufacturing plant with the aim of increasing the transparency on energy flows and recognizing the equipment that influences the consumption.

The different application contexts of the two case studies has allowed to fully validate the tool. It has been able to identify energy inefficiencies and what has generated them, both in a highly automated context and in a process with a high incidence of manual tasks. Then, the tool has been able to suggest improvement strategies to support decision making process. The difference between the two manufacturing systems has not affected the tool's effectiveness. In both case studies, the tool has supported the analysis and improvement process, leading to a considerable increase in efficiency and energy savings. Table 5.5 shows the results obtained from the implementation of the tool in the two case studies. Therefore, the tool could be applied to different factory system, covering a wide range of systems, processes and equipments.

Table 5.5: Energy savings and other advantages derived from the implementation of corrective actions in the two case studies

	Case Study I	Case Study II
Energy efficiency improved	+15%	+22%
Annual energy saving [kWh]	17170	116837
Annual CO_2 saving [kgCO_2e]	5615	38206
Annual cost saving [€]	2668.90	19862.26

The main advantage of the sEVM tool lies in the analysis and contextual identification of energy inefficiencies. In detail, the tool is able to quickly generate solution approaches to increase the energy efficiency in a factory system already during the production process. The tool detects the anomaly in real time and reports it to the user together with the cause. By this, the operator qualitatively analyses in real time the parameters that influence the energy inefficiency, enhancing the transparency on the energy consumption structure.

The introduction of the lean approach to the energy consumption analysis allows the user to easily identify the inefficiencies. The tool allows the allocation of energy consumption according to their contribution to value generation (i.e. value-added, non value-added and waste activities). Then, the data is visualized through appropriate indexes that allow to identify the inefficiencies of the production process. The employment of performance indicators based on the Lean methodology allows to easily identify the machines and the systems with high percentages of energy used for activities not related to VA. In the dashboard screen, the information is concentrated in the Process Box avoiding the information overload.

Process mapping and related metrics allow quantifying the gap between actual consumption and *"optimal"* consumption, understanding where the reduction of energy consumption is possible and which optimization strategies are the most suitable. Moreover, the hierarchical visualization displays energy data at different levels of detail, from the single machine tool and the production line to the whole factory plant. This feature allows all stakeholders involved in the production process (i.e. operators, energy manager and plant manager) to interact with the system and to improve the energy awareness.

These results demonstrate the usefulness of the proposed tool as a support for the energy management and decision-making process toward the maximization of the manufacturing system energy efficiency and minimization of correlated environmental impacts.

Chapter 6

Concluding Remarks

The present research work deeply investigated issues and opportunities related to energy efficiency management within the manufacturing context.

Energy efficiency is an important target for society as increasing energy consumption leads to negative climate effects. Manufacturing industry has a high share at the energy consumption, so enhancing energy efficiency is a significant objective with regard to economic and ecological issues in the sustainability context. Moreover, taking action to better manage energy consumption not only helps the planet, it saves money for organizations and society as a whole.

The state-of-the-art of scientific works indicate that there is a considerable potential to increase energy efficiency. Nevertheless, companies address barriers towards the implementation of these concepts that mainly derive from organizational (e.g., lack of time) and information-related aspects (e.g., lack of knowledge). In addition, a considerable amount of companies do not deduce improvement actions from energy efficiency audits. Therefore, it is essential to methodically support both the analysis of process energy efficiency and the identification of energy efficiency measures.

The proposed method overcomes the numerous literature works in the field of energy management, which are generally focused on increasing energy awareness rather than on the efficiency analysis. It combines the need to make the industrial process more sustainable with the potential of factory digitization. Through the intelligent interpretation of data, the method enables the monitoring and analysis of process energy efficiency and suggests corrective actions in case of inefficiencies. The main novelties of the method are the following:

- Allocation, representation and analysis of energies consumption according to their contribution to value generation. The final aim is to provide a useful means to minimize waste and improve efficiency by exploiting the established and widely used knowledge and procedures of the lean philosophy;

- Hierarchical approach to the problem with different zoom levels that allows performing a complete assessment of the factory systems both off-line and real time;

- Correlation of data related to energy, production and manufacturing activities to calculate specific, understandable, and effective KPIs, which easily allow identifying inefficiencies from an environmental and economic perspective. Moreover, the analysis results are displayed through an innovative, simple and clear dashboard to communicate insights to different stakeholders;

- Support in the definition of a concrete and feasible action plan to effectively address inefficiencies.

To support companies in the continuous improvement of energy performance, the proposed method has been then implemented in the smart Energy Value Mapping tool.

Automatic and continuous process data acquisition and data elaboration allow to simplify the tasks that the user has to address in the application of the method. The tool allows identifying and characterizing the energy flow to multiple levels (e.g., machine, line, plant) and detecting its value-added component. Moreover, it allows to suggest corrective actions to eliminate wasteful activities and reduce non value-added activities, from an energetic point of view.

Thanks to the tool, stakeholders can discover and recognize the inefficiencies related to production processes in real time, highlighting non value-added activities and unconsciously generated waste. It allows to instantly highlight the content of energy that is used to create value during the product manufacturing compared to the total amount of energy consumed by the factory. Finally, the mapping of the process through appropriate indicators and the developed algorithms support the decision-making process in the identification and implementation of corrective measures.

The sEVM tool performs a context aware monitoring of energy use in manufacturing systems. Unlike traditional monitoring systems, it provides not only raw/pre-processed data but also knowledge on process ambience. It increases the awareness of the process trend and performance, facilitating the decision-making process, and exploits the company's existing data, by retrieving and importing them from the management systems and displaying them in a clear and synthetic way through graphs.

The tool investigates the manufacturing process through both real-time and off-line analysis. When the tool detects an inefficiency in real time, it alerts the user so he/she can qualitatively analyse in real time the parameters that influence the energy inefficiency, enhancing the transparency on the energy consumption structure. In the off-line analysis, it allows to analyse energy efficiency over larger time periods (e.g., work shift, week, month, year), identifying anomalous trends and/or inefficiencies.

Taken together, the proposed methodology and tool represent a quantitative support for companies to monitor efficiency and energy consumption, and make informed decisions. According to company's stakeholders (i.e., plant manager, energy manager and process mangers) feedbacks, the method and tool answer the following factory needs:

- Energy flows and the relative 'users' are easily distinguishable;
- The process box and the map are user-friendly and contain essential data, avoiding the dashboard's infobesity. All other data, i.e., data collected from the process and data processed by the tool, are displayed on additional specific screens;
- The identification of the most critical areas is faster thanks to the developed indicators and the use of meaningful colors and graphical elements;
- The detection of inefficiencies is simplified and made less time consuming. The tool's notification of the anomaly allows stakeholders to intervene with a check only when necessary, instead of continuously monitoring the process data;
- The determination of the strategy for improving the manufacturing process is made easier thanks to the support of the tool. It suggests the most appropriate corrective actions to the user, facilitating the definition of the action plan.

The validation in two case studies has highlighted how the method and tool support all stakeholders in the process energy efficiency assessment. In both case studies, they have supported the analysis and improvement process, leading to a considerable increase in efficiency and energy savings. They are strategic tools that helps organizations put in place an energy management system and use their energy more efficiently and effectively.

The exploitation of the above-mentioned methodology and tool in industrial companies has shown how they contribute to addressing multiple Sustainable Development Goal (UnitedNations, 2015b). In detail, they help organizations to use energy more efficiently, through the development and implementation of an energy management system. This enables to address Goal 7, which promotes affordable and clean energy. In addition, by promoting responsible resource use and environmental conservation they meet, albeit partially, Goal 11 (i.e., make cities and human settlements inclusive, safe, resilient and sustainable) and Goal 13 (i.e., take urgent action to combat climate change and its impacts). Finally, they contribute to Goal 12 (i.e., responsible consumption and production) by reducing the environmental impact, promoting the energy efficiency and the use of renewable energy sources. In this way, they ensure sustainable consumption and production patterns.

Besides the positive results obtained, some general weak points of the proposed methodologies and tools have to be highlighted.

The first weakness concerns the data collection which strongly influences the analysis and the results accuracy. The implementation of the method in the sEVM tool allows to improve the acquisition phase. Indeed, it allows to capture data automatically and with reduced effort, simplify data processing and enable dynamic analyses. However, the accuracy of analysis results strictly depends on the information granularity. Many data collection devices are required to have accurate analyses. Energy meters have to be installed on each machine tool of the process, in addition to the connection with the available 'smart' equipments. Data collected from the company production control systems must also be detailed and at the same frequency as other data. If adequate input data is not available, the quality of the results will suffer and the tool will not be able to support the efficiency improvement process.

Moreover, the activities classification according to value is not an easy task, particularly for those companies that have not already implemented a lean production system. The latter goes beyond the isolated application of lean tools, it is a philosophy that should be shared and supported by all the company stakeholders. The full awareness of mission, pillars, procedures, tools, etc., should be ensured at each company level. Sometimes, this kind of change requires a lot of time and effort, and a change of mentality. Therefore, the effective implementation of the smart Energy Value Mapping method and tool could require a long-term perspective.

Another barrier that could limit the diffusion of this methodology and tool is certainly the absence of mandatory regulations related to the energy management. As described in Section 2.2.2, different regulations exist, but they are mandatory only for the energy intensive and large companies, while for all others there are no limits and/or regulations to follow. The introduction of energy management policies into a company is often a consequence of the entrepreneur's sensitivity to this issue. Hence, only with stricter regulation will it be possible to increase the energy efficiency and reduce the environmental impact of the whole industrial sector.

Although significant advances in comparison to the state of research has been made, there are diverse opportunities for future research, which would extend functionalities of the developed approaches and support incorporation in industrial business processes.

The developed method and tool would need to be extended to other processes. Additional efforts should be put to validate and verify the reliability and robustness of the proposed metrics and algorithms in heterogeneous production contexts (e.g., paper manufacturing, cement manufacturing, manufactures of food products, rubber and plastic product manufacturing, etc.).

Future works should also address the integration of other energy sources in addition to electricity, such as methane, heat, natural gas, oil, etc. Technically the implementation is not too difficult due to the flexible structure of the tool. This will allow to integrate the consumption and emissions of all energy resources employed by the production process, providing a holistic view of consumptions and a further perspective on sustainability in manufacturing.

In addition, the tool needs to be expanded to include the economic assessment of energy efficiency measures. The tool provides qualitative information of costs and benefits to support the decision-making and the measure implementation. However, investment decisions in practice usually require a detailed cost-benefit analysis. Hence, a possible extension of the tool must involve the development of an interface to a monetary assessment. The challenge of this task is to transfer the qualitative information into quantitative information in order to support the evaluation.

Another relevant improvement could be obtained by implementing machine learning algorithms in the developed tool. To improve the quality of decisions, the integration of artificial intelligence algorithms (e.g., Artificial Neural Network, Discriminant Function Analysis, Fuzzy Inference Engine, Least Squares Support Vector Machine, Genetic optimization algorithm, etc.) to support the identification of the cause and the related corrective action is a promising approach. This would improve tool's results accuracy and enable the usage of the tool also for users who are not experts in energy management.

Finally, another important direction of research could be the extension of the method and tool to environmental and social sustainability. The tool aims at increasing the energy efficiency of an enterprise. However, in a wider context, it could analyse process sustainability by extending the analysis to raw materials and human resources. Measures towards these goals could be integrated into the methodological approach. In addition, lean wastes already include inefficiencies related to human resources such as underutilised human capital and inadequate training. Consequently, this would entail the possibility to analyse the overall environmental sustainability of the production process and identify the parameters affecting it.

List of acronyms and abbreviations

BAT	Best Available Techniques
BREF	BAT Reference Documents
CI	Cost Index
CUSUM	Cumulative Sum
CPS	Cyber-Physical System
CO_2	Carbon dioxide
DEA	Data Envelopment Analysis
DM	Ministerial Decree
EnMS	Energy Management System
EnPI	Energy Performance Indicator
EVSM	Energy Value Stream Mapping
GDI	Gasoline Direct Injection Technology
HVAC	Heating, Ventilation, & Air Conditioning
IAC	Industrial Assessment Center
ICT	Information and Communication Technologies
IEA	International Energy Agency
IoS	Internet of Services
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
KPI	Key Performance Indicators
LLNL	Lawrence Livermore National Laboratory
MEFA	Material and Energy Flows Analysis
MEPS	Minimum energy performance standard
MI	Muda Index

NVA	Non value-added
PDCA	Plan-Do-check-Act cycle
R&D	Research & Development
SEC	Specific Energy Consumption
sEVM	smart Energy Value Mapping
SFA	Stochastic Frontier Analysis
SME	Small and Medium-Sized Enterprise
TBS	Technical Building Systems
UN	United Nations
UNI	Italian National Unification
US	United States
VA	Value-added
VSM	Value Stream Mapping
W	Waste

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