Sustainable life cycle and energy management of discrete manufacturing plants in the industry 4.0 framework

(Article begins on next page)

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Abstract:

Industry 4.0 (I4.0), through the digitalization and interconnection of manufacturing processes, can offer opportunities to improve production systems' sustainability. Despite the increasing number of scientific review papers related to I4.0 and production sustainability, most approaches and tools for sustainability evaluation lack of a tangible implementation framework.

The paper presents a framework that originated from the plant metabolism concept, a simplified version of industrial metabolism. It is based on Energy Material Flow Analysis (EMFA) and Life Cycle Assessment (LCA) tools for production plants' economic and sustainability assessment, using the I4.0 enabling technologies. A Multi-Criteria Decision Making (MCDM) method combines the two sustainability pillars for aiding companies in optimizing their production processes towards a reduction of energy/material flows. The combination of EMFA, LCA and MCDM tools into a plant metabolism-based model is the main novelty of this paper.

The framework consists of three main phases. The first phase allows to model the manufacturing system by defining the plant layout, the assets, and the input/output flows. The second phase allows gathering information from the manufacturing plant to assess environmental and economic Key Performance Indicators (KPIs) following the LCA principles. The third phase consists of post-processing results, minimizing specific KPIs for establishing the optimal production scenario.

A washing machine plant has been chosen as a case study to demonstrate the proposed method's capability in authentic contexts. Besides, the effectiveness in supporting companies in the analysis, identifying criticalities, and the proper energy and material flows management of production plants has been verified. Plant managers could use this framework for managing the production plans. From the scientific standpoint, the proposed method positively contributes to integrating the existing state of the art studies concerning the I4.0-related framework for the sustainability assessment and energy/material flows minimization of production systems.

List of Acronyms

CC	Climate Change
CED-NRE	Cumulative Energy Demand – Non-Renewable
CP	Cleaner Production
CPS	Cyber-Physical Systems
DES	Discrete-Event Simulation
EMFA	Energy Material Flow Analysis
EPD	Environmental Product Declaration
EPS	Expanded Polystyrene
FEP	Freshwater Eutrophication Potential
HDPE	High-Density Polyethylene
HH	Human Health
I4.0	Industry 4.0
I/O	Input-Output
ICT	Information and Communications Technology
IE	Industrial Ecology
IIoT	Industrial Internet of Things
IM	Industrial Metabolism
IoT	Internet of Things
ISO	International Organization for Standardization
KPIs	Key Performance Indicators
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
MCDM	Multi-Criteria Decision Making
MFA	Material Flow Analysis
MIG	Metal-arc Inert Gas
ODP	Ozone depletion Potential
PDCA	Plan, Do, Check, Act
PMF	Particulate Matter Formation
RA	Resources
SD	Sustainable Development
SDGs	Sustainable Development Goals
SM	Sustainable Manufacturing
TAP	Terrestrial Acidification Potential
TBL	Triple Bottom Line
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VSM	Value Stream Mapping
WM/WD	Washing Machines/Washer-dryers

List of Variables

CC_i	Unitary environmental impact of the i-th material
$CC_{Emission}$	Value of CC indicator at the n-th station for the Emission category
CC_{Fossil}	Value of CC indicator at the n-th station for the Fossil category
$CC_{Material}$	Value of CC indicator at the n-th station for the Material category
CC_{Other}	Value of CC indicator at the n-th station for the Other category
$CC_{Station\ "n"}$	Overall value of CC indicator at the n-th station
$CC_{Utility}$	Value of the CC indicator at the n-th station for the Utility category
CC_{Waste}	Value of CC indicator at the n-th station for the Waste category
$Cost_i$	Unitary cost of the i-th material
$Cost_{Fossil}$	Cost of the Fossil category items at the n-th station
$Cost_{Material}$	Cost of the Material category items at the n-th station
$Cost_{Other}$	Cost of the Other category items at the n-th station
$Cost_{Station\ "n"}$	Overall value of the Cost indicator at the n-th station
$Cost_{Utility}$	Cost of the Utility category items at the n-th station
$Cost_{Waste}$	Cost of managing Waste category items at the n-th station
KPI_i	Indicator selected for the optimisation problem
$M\_q.ty_i$	Quantity of the i-th material measured at a specific "process station";
Psc	Production scenario
Psc_optimized	Optimized production scenario
Psc_w	w-th feasible production scenario
Pse	Production set
Pse_k	k-th production set
Pta	Production target
T_f	Number of pieces produced in a given timeframe for a feasible production scenario
X%	Tolerance defined by the end-user for the optimization problem
X_z	z-th parameter necessary to characterize the k-th production set

1 Introduction

The 2030 Agenda for Sustainable Development (SD) of the United Nations outlines 17 Sustainable Development Goals (SDGs), and the member States are working towards their implementation. According to the Brundtland report (Brundtland 1987), Sustainable Development should accomplish the needs of the current generation without jeopardizing the rights and the capability of the next generations from the economic, environmental, social perspectives. The increasing consciousness of ecological problems forces industrial companies to reduce the environmental impacts of manufacturing processes and technical facilities by doing effective action plans (Fijał 2007; May, Stahl, and Taisch 2016). In Europe, the industry is responsible for 24% of the overall energy consumption (European Environment Agency 2020). The manufacturing industries are responsible for 20% of the greenhouse gas emissions produced by various economic activities (Eurostat 2021).

Industry 4.0 (I4.0), through the digitalization and interconnection of manufacturing processes, can offer opportunities to improve production systems' sustainability (Prathipati et al. 2021). Real-time energy and resources monitoring technologies, intelligent optimization algorithms and big data analytics promise benefits concerning product and process sustainability (Bonilla et al. 2018). Despite the increasing number of scientific review papers related to I4.0 and production sustainability, most of the frameworks and tools available for sustainability evaluation are more on a theoretical than on a practical level (i.e., they miss a tangible implementation framework). Useful tools leveraging these technologies and case studies concerning their application are recently suggested as future directions of research (Enyoghasi and Badurdeen 2021).

Industrial Ecology (IE) could represent an approach for process sustainability evaluation by integrating environmental and economic analysis. Energy Material Flow Analysis (EMFA) and Life Cycle Assessment (LCA) tools may enable the sustainability evaluation of industries. Multi-Criteria Decision Making (MCDM) methods are essential where the production planning should be optimized. Despite the importance of these approaches, methods and tools, and their stand-alone use, there are no approaches to integrating and applying them in an industrial context.

In this context, the paper presents a framework for the sustainable management of modern manufacturing plants for discrete production. The framework aims to evaluate the environmental and economic sustainability of multi-product production systems by using EMFA and LCA. The two methods allow to manage specific data, directly gathered from real-time measuring systems or general data, periodically measured, and then assigned to single production areas. An MCDM method combines sustainable Key Performance Indicators (KPIs) to find an optimized solution to schedule the production activities. The research deals mainly with the ninth (i.e., *industry innovation and infrastructure*) and twelfth (i.e., *responsible production and consumption*) SDGs.

The approach presented in this paper originates from the concept of plant metabolism, a simplified version of industrial metabolism. The framework consists of three main phases. The first phase allows to model the manufacturing system by defining the plant layout, the assets, and the input/output flows. The second phase allows gathering information from the manufacturing plant. Using life cycle principles, the framework assesses environmental and economic KPIs, which are strictly connected. Optimising a production system's environmental sustainability leads to economic benefits due to the minimisation of resource and energy consumption (Papetti et al. 2019). Social KPIs are beyond the scope of this work because quantitatively and objectively evaluating such metrics are still an ongoing research activity. The third and last phase of the framework consists of post-processing KPIs for establishing the optimal production scenario, driven by the minimization of sustainable KPIs, by using both a single-issue approach and a multi-criteria optimisation approach.

Results can be used as a decision aid model for managing production systems to address the sustainability targets fulfilling I4.0 features and requirements.

The framework has been used to evaluate the sustainable KPIs of a manufacturing plant producing washing machines. The final goal is to establish a production scenario that minimises resource consumption using a MCDM approach. The paper provides a tangible tool for implementing a sustainable manufacturing paradigm in an I4.0 environment. The framework can identify optimized production scenarios, minimising natural resources used by the plant while reducing the economic and environmental impacts.

Through this method, process sustainability becomes a new driver that plant managers could consider for managing the production schedule. From the scientific point of view, this framework is a tangible representation of an approach to collect, manage, elaborate, and interpret data toward sustainable manufacturing. The paper demonstrates that in the I4.0 paradigm, Industrial Ecology, EMFA, LCA and MCDM can be effectively integrated into a framework usable within industrial scenarios.

The rest of the paper is organised as follows. Section 2 presents sustainable manufacturing and reviews state of the art concerning methodologies, tools and KPIs about I4.0 and sustainability in manufacturing systems. Section 3 presents the proposed plant metabolism method and the framework for its implementation. Section 4 shows the method's application in a home appliance manufacturing plant case study and discusses the obtained results, method potentialities, and implications from the scientific and managerial perspectives. Finally, section 5 concludes the paper by summarising outcomes, discussing limitations of the approach and proposing future research directions.

2 State of the art

2.1 Theoretical background concerning sustainability in manufacturing systems

2.1.1 Methodological approaches towards sustainability in manufacturing and production

Sustainable development is implemented through sustainable manufacturing (SM) methodology in the industrial sector. SM deals with producing economically sound products realised through healthy manufacturing processes for employees and preserving energy and natural resources. SM is a research area that has attracted researchers and practitioners since the early years of 2000. Nevertheless, there are still different definitions of SM (Moldavska and Welo 2017). The analysis of these definitions allows to highlight that SM covers several disciplines such as (i) product design (Lacasa, Santolaya, and Biedermann 2016), (ii) process design and operational principles (Jovane et al. 2008), (iii) material/energy/waste flows analysis (Kaebernick, Kara, and Sun 2003)(Cassettari et al. 2017), (iv) supply chain management (Jayal et al. 2010), and (v) all the other aspects related to the optimisation and planning of production activities (S. Wang et al. 2015). SM is conceived as an extensive methodology that needs to be supported by applicative methods and tools to aid managers and practitioners in strategic and operative decisions (Gong et al. 2018).

Industrial ecology (IE) was the first attempt to implement the SM principles, emphasising environmental and social sciences. According to IE, industries behave as natural ecosystems, where materials and energies are used by organisms (El-Haggar 2007). IE focuses on the material, energy and information flows, including exchanges between the industries and other entities (e.g., society, government). Lowe and Evans (Lowe and Evans 1995) formalised IE's concept as a multidisciplinary approach referred to a globally organised closed-cycle economy. Therefore, IE can be considered a broad framework that guides the transformation of industrial systems towards sustainability.

Based on the IE principles, Ayres and Simonis (Ayres and Simonis 1994) introduced the theory of Industrial Metabolism (IM). IM's meaning is to apply the concept of "*metabolism*", known in the biological context, to the industrial world, assuming that manufacturing/production sites are analogue to a living organism in biology. IM considers the interaction between industrial systems (manufacturing plants) and the external world in economic and physical flows (Wassenaar 2015).

Cleaner Production (CP) is a practical approach toward SD (Al-Yousfi 2004). CP provides a framework for evaluating industries' environmental impacts and putting into practice those strategies to reduce such adverse effects. It involves studying the interactions and relations between industrial and ecological systems (Fan et al. 2020). CP emphasises a preventive approach to environmental management, considering impacts over products and services' whole life cycle (Bras 1997) (McIntyre, Ivanaj, and Ivanaj 2013).

2.1.2 Tools related to sustainability in manufacturing and production

The previously mentioned methodologies embrace several tools used for sustainability evaluation. The most relevant are material flow analysis (MFA), value stream mapping (VSM) and LCA (Menghi et al. 2019).

MFA allows to systematically evaluate materials flows and stocks (and energy, in the EMFA version) within a complex system with well-defined space and time boundaries (Brunner and Rechberger 2004). Even if it has become an integral part of many environmental impact statements/assessments, through an MFA study, a system's environmental impacts cannot be quantified (Favi et al. 2016). For this reason, if used stand-alone, MFA shows some practical limitations.

VSM is another analysis tool that enables companies to focus on value-added and non-value-added activities. Consequently, enterprises can identify hidden wastes and sources of waste in manufacturing (Haefner et al. 2014). Although VSM is a valid approach to describing single or interconnected processes, it does not catch all aspects of sustainability (e.g., emissions, costs, social factors).

LCA is one of the most comprehensive approaches and tools used for the environmental assessment of products, services and human activities. However, LCA is a complex science that shows several limitations in manufacturing plants analysis and management. LCA is time-consuming and resource-intensive (Rossi, Germani, and Zamagni 2016). It requires a high degree of expertise, and it does not allow a dynamic analysis considering the evolution of production (e.g., batch size, product models and families).

2.1.3 Key performance indicators

Sustainable manufacturing models and tools require the definition and use of specific KPIs dedicated to evaluating performance, correct management and scheduling of manufacturing plants (Mani et al. 2014), (Rodrigues, Pigosso, and McAloone 2016). Different metrics have been adopted in this context. The standard practice in manufacturing is to use measurable flows of materials and energy as KPIs. Raw material consumption, energy consumption, airborne emissions, liquid and solid wastes are typical indicators used in literature studies (Deif 2011), (Jiang, Zhang, and Sutherland 2012), (May, Barletta, et al. 2015). However, adopting these indices requires the correct management of information by production experts, such as plant managers or manufacturing engineers.

Due to the different sustainability aims, KPIs for sustainable manufacturing have been generally used in an unstructured manner. They are used as stand-alone indicators. Only a few examples attempt to provide an overview and classification of quantitative KPIs used to address and correlate the various aspects of sustainability in manufacturing systems (Joung et al. 2013), (Hristov and Chirico 2019). Based on the different sustainability and sustainable production pillars, the literature on environmental and economic KPIs assessment is quite broad. Only a few works tried to introduce numerical KPIs related to the social part. Indeed, social outcomes are qualitative suggestions and guidelines (Lehmann et al. 2013; Weidema 2005) rather than numerical indices for environmental and economic analyses.

2.2 Sustainable manufacturing in the Industry 4.0 context

I4.0 was first defined in 2011 by German researchers (Kagermann et al. 2013) for maintaining the German economy's future competitiveness. I4.0 aims to connect resources, services, and humans in real-time, through Cyber-Physical Systems (CPS) and the Internet of Things (IoT).

Sustainability is commonly assessed through the Triple Bottom Line (TBL) framework, consisting of social, environmental, and economic pillars. Social sustainability refers to the equitable inclusion of human resources, considering social classes, gender, age groups, and cultural identity (Tim Stock et al. 2018), (Ben Ruben, Menon, and Sreedharan 2018). On the other hand, environmental sustainability describes the preservation and survival of the ecological system (Tim Stock et al. 2018). Economic sustainability refers to an economy's ability to consistently maintain a respectable level of increasing domestic productivity over a long period (Rogers and Daly 1996).

Recent scientific surveys concerning I4.0 and sustainable development highlight relationships between these topics (Machado, Winroth, and Ribeiro da Silva 2020). I4.0 provides several opportunities toward SD (Demartini, Evans, and Tonelli 2019), (T. Stock and Seliger 2016), (Machado, Winroth, and Ribeiro da Silva 2020) by overcoming the lack of integration between product-process-system, inability to real-time management information, and the absence of integrated multi-criteria tools for performance evaluation and optimization (Enyoghasi and Badurdeen 2021). I4.0 can be enabled through nine technologies: *big data*, *optimization and simulation*, *cloud computing*, *virtual and augmented reality*, *system integration*, *IIoT* (Industrial Internet of Things), *additive manufacturing*, *autonomous robots*, and *cybersecurity* (Rüßmann et al. 2015). Most of these technologies have a potential impact on sustainability. In particular, *IIoT*, *big data* and *optimization/simulation* are the three most relevant ones (Enyoghasi and Badurdeen 2021).

IIoT technology refers to information technology infrastructures that collect and transmit data between devices to identify, localise, track, and monitor objects (de Sousa Jabbour et al. 2018). As stated in (Bonilla et al. 2018), *IIoT* guarantees sustainability benefits. The adoption of intelligent assets and monitoring systems allows measuring each flow inside a plant (Kagermann et al. 2013). Besides, industries have developed information and communications technology (ICT) infrastructures able to cope with the issue related to data acquisition and management (Germani et al. 2014). *Big data* technology contributes to increasing the net profit through its forecasting capability that allows efficient resource utilization (Wee et al. 2015). *Optimization and simulation* can also optimize manufacturing processes, reducing energy consumption and environmental impact (Claudia Pereira Carvalho, Paula Pereira Carvalho, and Gabriela Pereira Carvalho 2020).

I4.0 opportunities and challenges refer to the three pillars of sustainability, as stated by Muller et al. (Müller, Kiel, and Voigt 2018), that presented a research model based on TBL comprising I4.0. Environmental sustainability is the most important dimension that can benefit from I4.0 technologies. I4.0, through real-time monitoring of production data, improves the awareness of resources consumption and their allocation, including water, energy and raw material (Bonilla et al. 2018) (Ejsmont, Gladysz, and Kluczek 2020) (Kamble, Gunasekaran, and Gawankar 2018) (Shrouf and Miragliotta 2015). Furthermore, intelligent optimization algorithms with big data processing platforms can optimize total energy consumption (Bonilla et al. 2018; May, Stahl, et al. 2015) and carbon footprint (Fang et al. 2011). For example, companies may schedule their energy-intensive tasks when there is an oversupply of available energy (Kamble, Gunasekaran, and Gawankar 2018). Researchers are looking for frameworks aiding companies in managing production to minimize energy consumption through IIoT and big data.

From an economic standpoint, I4.0 can significantly reduce the total cost of ownership of production plants adopting predictive maintenance and offering highly customized on-demand manufacturing (Kamble, Gunasekaran, and Gawankar 2018). Benefits also concern the social dimension of I4.0. For example, employees can benefit from enhanced human learning through intelligent assistance systems and human-machine interfaces, leading to increased satisfaction in industrial workplaces (Müller, Kiel, and Voigt 2018). Despite the abovementioned advantages of I4.0, it is worth noting that some drawbacks need to be evaluated. For example, an increased production rate, possible thanks to industrial automation, would be associated with higher resource and energy consumption and elevated pollution concerns (Ghobakhloo 2020). Furthermore, smart production systems will require massive data centres to process and support their network needs (Bonilla et al. 2018).

2.3 Methods and tools for sustainable manufacturing in Industry 4.0 context

During the last years, several frameworks and tools have been developed in sustainable manufacturing, and most of them are based on MFA (or EMFA, whether also considering energy). In reference (Sendra, Gabarrell, and Vicent 2007), authors developed an EMFA tool in the context of Industrial Ecology, which was used for evaluating the efficiency of industrial areas through a set of indicators (e.g., direct material input, total material requirement, worker productivity, eco-efficiency, eco-intensity). The paper does not present the method to collect data from production lines or discuss process optimisation. EMFA was also used in (Teresa Torres et al. 2008) for evaluating the sustainability of manufacturing roof tiles in the ceramic industry. The paper is focused on presenting the case study, and the proposal does not seem general to be used in other industrial sectors. This paper is not giving the benefits of I4.0 toward sustainability.

Value Stream Mapping is another tool used for evaluating sustainability. VSM can be employed to assess energy consumption, thus the environmental sustainability of a production process, as discussed in (Garza-Reyes et al. 2018). The authors combined VSM with the PDCA (Plan, Do, Check, Act) method to continuously improve environmental sustainability (not economic sustainability). The benefits of sensorized production lines and optimisation algorithms are not available. An extended version of the VSM tool is presented in (Alvandi et al. 2016). The authors developed a methodology (E^2VSM) for evaluating the environmental and economic sustainability of multi-product manufacturing systems. Gathering flows of material and energy directly from production machines, the method enables what-if analysis for improvement measures. The paper does not provide any mathematical approach to solve the optimization phase of a manufacturing process.

Life Cycle Assessment is another tool used to evaluate the process sustainability (even if it does not usually measure manufacturing processes' environmental performance). Life cycle assessment is employed in different manufacturing sectors from the sustainable manufacturing aspect (Ranjan, Agrawal, and Jain 2021). The LCA method presented in (Löfgren and Tillman 2011) was coupled with a Discrete-Event Simulation (DES) tool to optimize manufacturing systems' environmental sustainability. Economic sustainability is not addressed. DES tools are undoubtedly valuable for modelling and simulating manufacturing processes to evaluate environmental aspects (Thiede et al. 2013).

Moreover, (Thiede et al. 2016) tried to integrate VSM, LCA and EMFA tools into a specific methodology for analysing energy, material, and time flows of manufacturing systems. Besides the novelties of such a paper, the authors do not present how data are gathered from the production processes or any optimisation method.

Multi-criteria optimization tools could help companies evaluate the three pillars of sustainability and optimize their manufacturing processes (S. Singh, Upadhyay, and Powar 2022). MCDM methods are widespread in sustainable manufacturing. Among the available approaches (Jamwal et al. 2021), most of the studies available in the SM area are based on fuzzy-based single modes. To balance production and green sustainable development, (Peng et al. 2021) presented a multi-objective flexible job shop scheduling problem model constrained by job transportation time and learning effect. A relevant framework for sustainable manufacturing is shown in (Saad, Nazzal, and Darras 2019). It aims to evaluate manufacturing processes' sustainability while proposing the most effective techniques for ensuring a robust assessment. The framework, which does not tackle I4.0 enabling technologies, lacks any application into the industrial sector. Another method for evaluating economic and environmental sustainability is presented in (S. Zhu et al. 2017). The selection of the best manufacturing system is performed through a decision-making model to maximize the process chain's carbon efficiency. Even if the proposal's novelties are clear, the case study demonstrates its application to the manufacturing process of a single component (the application to a multi-product is not addressed). Another paper using a multi-criteria approach for evaluating manufacturing process sustainability is presented in (Bruzzone et al. 2012). Here the focus consists in integrating energy-aware scheduling and advanced planning and scheduling systems.

A recent paper addressing the benefits of I4.0 for sustainable manufacturing (Enyoghasi and Badurdeen 2021) highlights that I4.0 benefits and challenges described in almost all the literature reviews are based on theoretical assertions rather than actual observations. In the same paper, the authors suggest pushing the research towards case studies about applying I4.0 technologies to improve process sustainability.

2.4 Current limitations and proposed novelties

The literature analysis highlights potential shortfalls in the sustainable management of manufacturing plants. Most of the recent paper's present frameworks for manufacturing sustainability, but, alternatively, they lack in one or more of the following aspects:

- Integration of environmental and economic analyses based on the Industrial Ecology approach.
- Integration of EMFA and LCA tools for sustainability evaluation.
- Adoption of MCDM models for optimising the production planning following changes of production conditions (e.g., production rate).
- Management of multi-product and complex (combination of multiple production machines) production systems.
- Adoption of IIoT, big data and optimization enabling technologies of I4.0 for real-time data acquisition.

The paper presents a framework, based on EFMA and LCA tools, for the economic and sustainability assessment of production plants, using the enabling I4.0 technologies (IIoT, big data and optimisation). An MCDM method is used for combining the two sustainability pillars for aiding companies in optimizing their production processes.

3 Method

This section presents the framework for sustainable management of manufacturing plants in compliance with the I4.0 paradigm and the related plant infrastructure (e.g., machines, equipment, embedded sensors, ICT systems, IIoT infrastructure). However, the context of I4.0 is not a limitation of the methodology, and it can also be implemented in cases of "traditional" plants (not sensorized machines).

The method is based on the concept of industrial metabolism, firstly developed by Ayres and Simonis (Ayres and Simonis 1994) and subsequently modified in a previous work of the same authors (Favi et al. 2016). The new model, called "*plant metabolism*", is a simplified version of the industrial metabolism concept. In "*plant metabolism*", the complex interaction between the different industrial activities in a more extensive system has been limited in time (plant life cycle) and space (plant gate). The reason behind this limitation concerns the possibility to classify each item of plant activities for the subsequent assessment. Inputs and outputs of the "*plant metabolism*" model have been characterised based on literature review on this topic, and following the standard practice observed in industries (Joshi 1999), (Xue, Kumar, and Sutherland 2007), (Kellens et al. 2012), (Duflou et al. 2012), (Magnusson, Andersson, and Ottosson 2019). The proposed model of "*plant metabolism*" is depicted in Figure 1.

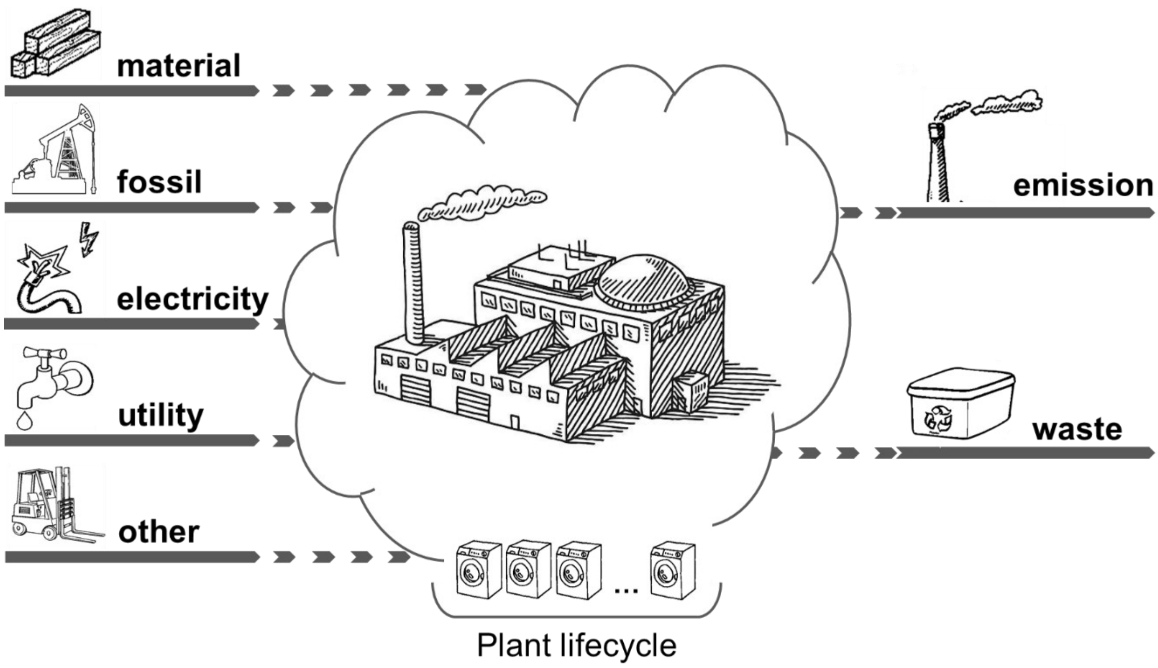

Figure 1: Plant metabolism model (based on Favi et al., 2016).

The plant life cycle is strictly connected with the manufactured product and the plant evolution in plant metabolism. The way to define a temporal life cycle for a plant requires the definition of a rule: "*the plant life cycle is considered the timeframe between the change of specific product technology, which is independent of the product models under manufacturing; or the timeframe between two important plant upgrades which involves the equipment and infrastructures*". To better explain the concept of "product technology", the example of TV manufacturers can be provided. In this context, the shift from the cathode-ray tube to LCD technology is considered. This change is deemed disruptive and irreversible; thus, a comprehensive reorganisation of the plant is required, including equipment, layout and machines. On the other hand, considering the same product technology (i.e., LCD), several product families with different dimensions set (e.g., 22, 40, 50 inches) or features (e.g., HD, smart TV, 3D) can be manufactured.

The plant system boundary is temporally defined from the birth of the new technology to the end of the same technology. The gate of the facility represents the spatial boundary. Considering these definitions, the plant can be defined as a black box with different flows (see Figure 1 for plant metabolism). Plant inputs are summarised as *material*, *fossil*, *electricity*, *utilities,* and *others*. Plant outputs are summarised based on the different pollutions released to the environment: *emission* and *waste*. It is worth noting that the product is not considered a system output because it results from the manufacturing process (digestion and absorption of nutrients, according to the plant metabolism approach). Instead, the material scraps (i.e., materials that do not constitute the final mass of the product) are considered system outputs (*waste*) because they are used during the manufacturing process. Still, they will not take part in the final product (digestion scraps).

3.1 KPIs definition

A set of KPIs has been chosen to give a comprehensive picture of the manufacturing plant, including the main aspects of sustainability. The definition of KPIs follows the guidelines proposed by the International Organization for Standardization (ISO), within the standards of the 22400 series (ISO 2014a; ISO 2014b), which provide the basis to characterize KPIs in manufacturing and production. Adopting a standardized way for the definition of KPIs and making them uniform brings benefits for the industry, allowing comparison between different companies and long-term reviews. Moreover, relevant reviews of previous studies focused on manufacturing performance indicators and sustainable manufacturing indicators, have been used by authors to finally develop a set of KPIs for sustainable manufacturing evaluation (Hristov and Chirico 2019; Lucato, Santos, and Pacchini 2017; Zackrisson et al. 2017; Kibira et al. 2018).

KPIs have been classified in (i) Primary KPIs, which include *Resource consumption KPIs*, and (ii) Secondary KPIs, which include both *Environmental KPIs* and *Economic KPI* (Figure 2). The distinction between primary and secondary KPIs deals with how they are assessed. Indeed, Primary KPIs are directly evaluated by the input-output (I/O) analysis of the plant and are considered manufacturing performance indicators (resource consumption). At the same time, secondary KPIs result from mathematical operations combining primary KPIs and unitary environmental impacts and cost items (background data). Secondary KPIs have adopted the double bottom line of sustainability consisting of environmental and economic performance factors. The choice to adopt two levels of KPIs (primary and secondary) is based on the possibility of addressing multiple aspects involved in the plant analysis, leading the user to select the suitable KPIs based on the scope of the specific study.

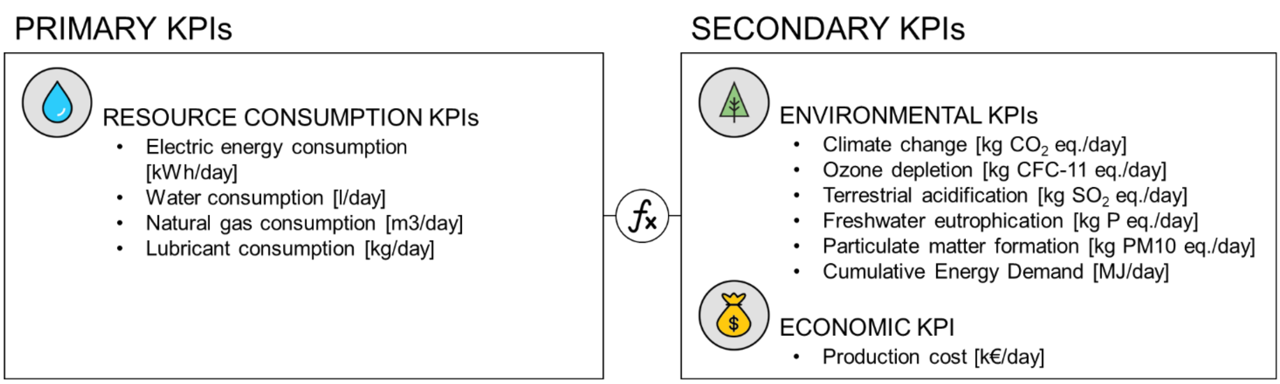

Figure 2: KPIs of the proposed model

Concerning resource consumption KPIs, the assessment of principal utilities has been used for this purpose. Resource consumptions are calculated by analysing the plant's utilities, which are discretised at each machine/station to have a detailed analysis of the manufacturing process and the resources required by each process. Several research works have been analysed to define primary KPIs following different industrial contexts (Kellens et al. 2012; Amrina and Yusof 2011; K. Singh and Sultan 2018; Cristea and Cristea 2021; Shahbazi et al. 2017; Q. Zhu et al. 2015; Favi et al. 2017; Diaz C. and Ocampo-Martinez 2019; Gontarz et al. 2015; Longo et al. 2016). Table 1 reports the primary KPIs used to analyse resource consumption in a manufacturing plant.

Table 1. List of primary KPIs used for plant analysis

Primary KPI	Unit	Reason	References
Electric energy consumption	kWh	Electric energy is a plant metric, and it can either be measured directly (e.g., with power meters) or estimated. Electric energy is a cost-effective indicator and easily understandable for different company members and external stakeholders. Electric energy is highly relevant and comparable with historical data. Electric energy strongly relates to environmental pollutions (i.e., CO_2 emissions). Electric energy has a relationship with sustainability goals (i.e., sustainable development goals).	[Kellens, 2012] [Amrina, 2011] [Singh, 2018] [Cristea, 2021] [Zhu, 2015] [Favi, 2016] [Favi, 2017] [Diaz, 2019] [Litos, 2017] [Longo, 2016]
Water consumption	litre	Water consumption is a plant metric, and it can either be measured directly (e.g. with water flow meter) or estimated. Water consumption is a cost-effective indicator and easily understandable for different company members and external stakeholders. Water consumption is hugely relevant and comparable with historical data. Water consumption strongly relates to environmental pollutions (i.e., marine and freshwater eutrophication). Water has a relationship with sustainability goals (i.e., sustainable development goals).	[Amrina, 2011] [Singh, 2018] [Favi, 2016] [Favi, 2017]
Natural gas consumption	m^3	Natural gas consumption is a plant metric. It can be measured directly (e.g. with a gas flow meter) or estimated. Natural gas consumption can be a cost-effective indicator for some discrete plants and easily understandable for different company members and external stakeholders. Natural gas consumption is important and comparable with historical data. Natural gas consumption strongly relates to environmental pollutions (i.e., CO_2 emissions).	[Amrina, 2011] [Zhu, 2015] [Favi, 2016] [Favi, 2017] [Diaz, 2019] [Litos, 2017]
Lubricant consumption	kg	Lubricant consumption can be easily estimated. Lubricant consumption is important and comparable with historical data. Lubricant consumption strongly relates to environmental pollutions (i.e., terrestrial acidification).	[Amrina, 2011] [Shahbazi, 2017] [Gontarz, 2012] [Favi, 2016] [Favi, 2017] [Diaz, 2019]

Concerning environmental KPIs, the LCA method has been used (ISO 14040 – ISO 14044) (ISO 2006a)(ISO 2006b) for this purpose. Environmental KPIs are calculated using specific life cycle impact assessment (LCIA) methods available in literature such as:

- ReCiPe midpoint – Hierarchist (H) version – Europe (Goedkoop et al. 2009) (Huijbregts et al. 2017);
- Cumulative Energy Demand (CED) (Roland and Weidema 2010).

The selection of the most suitable LCIA method is related to the system's characteristics under analysis. Since this study is oriented towards assessing environmental loads in industrial manufacturing, materials, energy, and natural resources are the most relevant flows. Besides, the mentioned indicators have been considered in related research works focused on the same aim (Joshi 1999), (Jacquemin, Pontalier, and Sablayrolles 2012), (Kellens et al. 2012), (Rodrigues, Pigosso, and McAloone 2016), (Dorn et al. 2016), (Abreu, Alves, and Moreira 2017), (Litos et al. 2017), including a set as mandatory parameters to control in industrial production/manufacturing by international and communitarian directives (UN, 1993; EU, 2010). This study uses midpoint impact categories connected to the Human Health (HH) and Resources (RA) end-point impact categories as described in the ReCiPe document report (Goedkoop et al. 2009). The default ReCiPe midpoint method perspective used is the Hierarchist (H) version. This choice has been made based on the most common policy principles concerning the 100 [years] timeframe (as referenced in the ISO 14044:2006 standards on LCA).

Table 2 reports, firstly the list of environmental KPIs, in particular: (i) ReCiPe midpoints indicators that have been chosen for the characterisation of different plant emissions to the environment, and (ii) Cumulative energy demand (CED-NRE) non-renewable indicator used as a single-issue indicator to gather the different energy sources required by the plant. In the case of a particular manufacturing plant (e.g., chemical industry), specific additional environmental indicators (e.g., human toxicity) should be considered and included within the frame of the ReCiPe impact assessment method. Such modification constitutes a customisation of the LCA model based on the specific needs of the plant under analysis. Concerning economic KPIs, only one indicator has been adopted for this aim (Table 2). The production cost [k€] is a clear and comprehensive indicator to describe the economic aspect of production sustainability.

Table 2. List of secondary KPIs used for plant analysis

KPI type	Secondary KPI	Unit	Reason	References
Environmental	Climate change (CC)	kg CO2 eq	Most common indicator to consider the influence of the factory activities on climate changes such as the global warming	[Hristov, 2019] [Dorn, 2016] [Favi, 2016] [Favi, 2017] [Amrina, 2011] [Singh, 2018] [Litos, 2017]
	Ozone depletion (ODP)	kg CFC-11 eq	Important indicator related to the air emission-reducing the ozone layer	[Dorn, 2016] [Favi, 2016] [Favi, 2017] [Singh, 2018] [Litos, 2017]
	Terrestrial acidification (TAP)	kg SO2 eq	Important indicator related to the air emission and acid rains	[Dorn, 2016] [Favi, 2016] [Favi, 2017] [Singh, 2018] [Litos, 2017]
	Freshwater eutrophication (FEP)	kg P eq	Important indicator related to the freshwater emission	[Dorn, 2016] [Favi, 2016] [Favi, 2017] [Singh, 2018] [Litos, 2017]
	Particulate matter formation (PMF)	kg PM10 eq	Important indicator related to the dangerous air emissions for human health	[Dorn, 2016] [Favi, 2016] [Favi, 2017] [Singh, 2018]
	Cumulative Energy Demand – Non-renewable (CED-NRE)	MJ	Important indicator to account non-renewable resource consumption	[Hristov, 2019] [Favi, 2016] [Favi, 2017] [Abreu, 2017]
Economic	Production cost	k€	Most common indicator to quantify the overall cost of the production system	[Hristov, 2019] [Favi, 2016] [Favi, 2017] [Singh, 2018]

It is worth noting that KPIs oriented to social sustainability have not been included in this list. Currently, the available methods and standards are not providing a quantitative assessment of social indicators (e.g., workers equality/inequalities, poverty) to link with the production scheduling/planning (Cadena et al., 2019). Besides, social LCA uses generic and site-specific data that can be either quantitative or qualitative (Ben Ruben, Menon, and Sreedharan 2018). Social assessment can be considered a voluntary, non-regulatory instrument that aims at self-regulation and corporate responsibility more than tangible support for production scheduling (Tsalidis et al. 2021). However, methodological frameworks and metrics will also be available for the social pillar of sustainability. They can be integrated as complementary KPIs in the proposed framework. Other KPIs related to the quality of the work environment (e.g., O_2%, CO_2%; VOC %, noise level, light level) and usually linked with the social part of sustainability (i.e., working environment) are managed by the plant engineer regardless the production management with the aim to keep them below a given threshold (Husgafvel et al. 2015).

3.2 Framework for KPIs evaluation and optimisation

Implementing the proposed method requires a structured framework for collecting data from the plant and providing a quick answer about the most appropriate production scheduling towards sustainability. The framework includes three main phases, as proposed in Figure 3:

1. *System modelling*, which allows drafting life cycle inventory (LCI) using a structured framework.
2. *Data processing*, which allows real-time calculation of life cycle KPIs using the inventory data.
3. *Results post-processing*, which allows elaborating the obtained results to support decision-making strategies towards sustainable management of production systems.

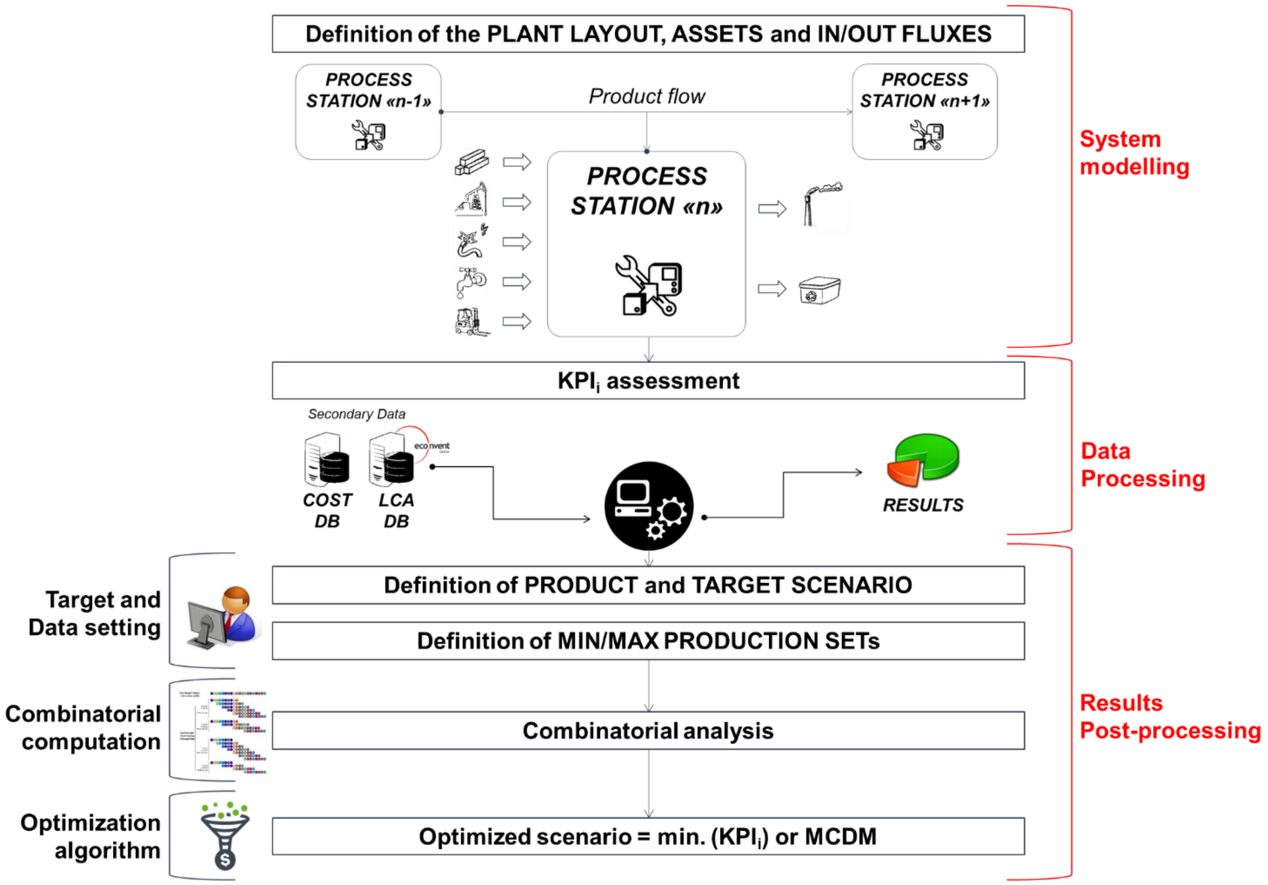

Figure 3: Framework overview of the proposed model.

3.2.1 System modelling

The system modelling phase allows classifying each I/O plant flow to refer the flows to each process station. The different granularity levels of the analysis are crucial for the proposed approach, allowing plant discretisation based on the plat manager needs. The system modelling phase works as a data framework for the I/O flows inventory. The data framework has been developed starting from the literature analysis (Xue, Kumar, and Sutherland 2007), (Kellens et al. 2012), (Duflou et al. 2012) and observing successfully case studies of sustainable manufacturing and I4.0 implementation in different fields (e.g., household appliances, automotive, textile and shoes) (Pezenatto et al. 2020). Table 3 reports a detailed classification of the I/O flows related to a generic "*process station*", defined as a machine, a production area or a plant department. The plant engineer performs plant discretisation related to the final objective of the analysis: (i) a holistic assessment of the plant itself or (ii) a detailed map of each machine/area.

Table 3. I/O flows classification for each "process station" (extract from Favi et al. (2016) and modified for the I/O modelling)

Flow type	Category	Sub-category	Description
Input	Material	Raw Materials	Excess of materials (material scraps) that are not used within the product (e.g., carbon steel, aluminium alloy) and consumed in a process station
		Pure Materials	Excess of accessory materials (material scrap) that are not used within the product (e.g., zinc, chromium) and consumed in a process station
		Chemical Agents	Chemical substances used within a manufacturing process and consumed in a process station (e.g., phosphoric acid, degreasing agents)
		Gases	Gases used within a manufacturing process and consumed in a process station (e.g., Ar, He, O_2)
	Fossil	Fossil fuels	Fossil fuels used within a manufacturing process and consumed in a process station (e.g., methane, diesel)
	Electricity	Electric energy	Electric energy used within a manufacturing process and consumed in a process station
	Utility	Air	Compressed air used within a manufacturing process and consumed in a process station
		Water	Water used within a manufacturing process and consumed in a process station, including its origin (e.g., tap water, river water)
	Other	Maintenance	Maintenance items for scheduled and extraordinary machine part replacement (e.g., materials, energy, machine components)
		Consumables	Consumables used within a manufacturing process and consumed in a process station
		Transport	Fossil fuels used for transports and consumed in a process station
Output	Emission	Gaseous emission	Gaseous substances emitted to eco-sphere from a process station
		Liquid emission	Liquid substances emitted to eco-sphere from a process station
	Waste	Industrial waste	Solid wastes generated within a process station (e.g., packaging of materials, papers) and emitted to eco-sphere

Identifying all the necessary flows to consider in the analysis is an essential prerequisite to performing the KPIs assessment of a production plant. Following the concept of plant metabolism previously described, I/O flows related to plant activities must be considered in the analysis. A general schema for the I/O flows representation, and the information collection is reported in Figure 4.

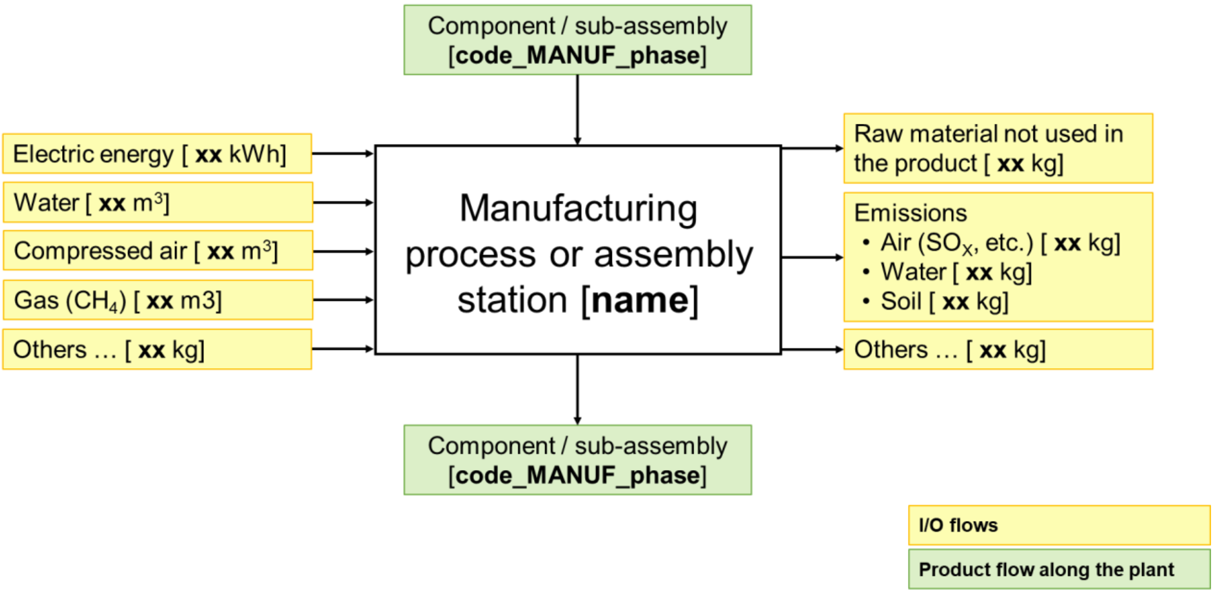

Figure 4: Schema for I/O flows data collection.

The I/O flows can be measured by using embedded sensors that are part of the infrastructure (smart assets) developed in the context of I4.0. These sensors measure the mentioned flows with the desired level of granularity by following the plant discretisation. Using a dedicated ICT infrastructure, I/O flows can be collected and managed within a central system (a company repository). Smart assets and ICT infrastructure are integrated to create a network of interactive elements with physical inputs and outputs that can be considered a cyber-physical system. However, the definition of these assets and the development of ICT infrastructure are not the topic of this work, and they are not debated in detail. In cases where the ICT infrastructure is unavailable, the I/O analysis can be carried out based on historical data and other collected information. The outputs of the *System modelling* module are:

- The discretisation of the manufacturing plant based on the desired level of granularity.
- The quantification of I/O flows for each "process station" based on the defined classification.
- The storage of I/O flows data in a company repository for subsequent management and elaboration.

3.2.2 Data Processing

The *data processing* phase aims to perform the plant sustainability analysis with the assessment of defined KPIs. I/O flows represent the primary data directly coming from the factory; however, it is necessary to correlate them with secondary data to calculate the environmental impacts. *Ecoinvent* database has been used to build a repository containing secondary data for unitary environmental impacts (*LCA DB*). Internal company knowledge and economic data have been used to create unitary material/energy costs (*COST DB*). The actual consumption of resources is directly calculated (primary data) by managing data retrieved from the plant and collected using the ICT infrastructure developed for the I4.0 model. Primary data (from the production plant) and secondary data (from DBs) are the input of specific equations to calculate the described KPIs (according to the relationships shown in Figure 5). Results can be presented both numerically and graphically.

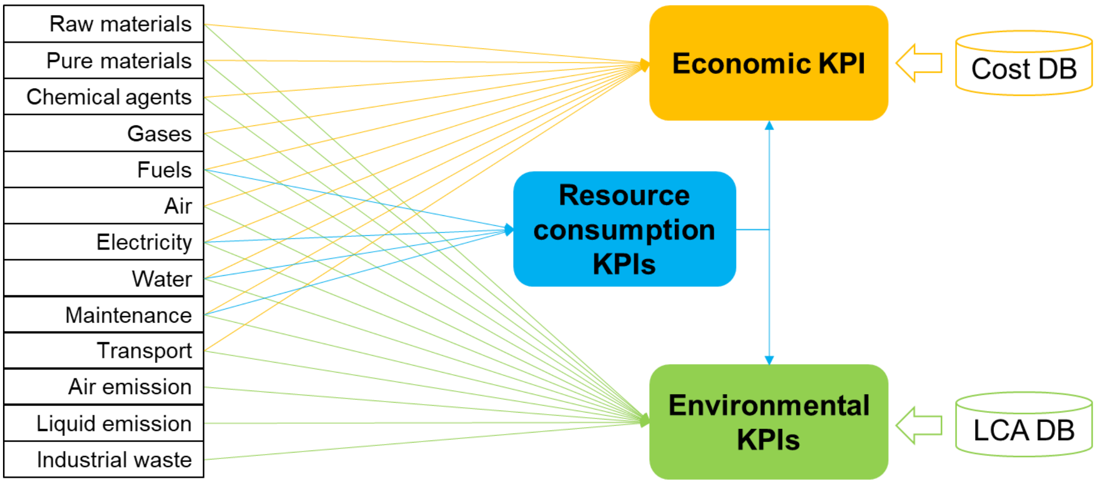

Figure 5: Relationships between primary data (on the left), secondary data (on the right) and the defined KPIs.

Concerning resource consumption KPIs, each indicator is calculated as a sum of flows (I/O) for each process station. For environmental KPIs, each indicator is evaluated as a sum of flows (I/O) to each process station. As an example, Equation 1 is used to calculate the Climate Change (CC) indicator for a generic station "n".

$$CC_{Station\ "n"} = CC_{Material} + CC_{Fossil} + CC_{Utility} + CC_{Other} + CC_{Emission} + CC_{Waste} \qquad \text{(Equation 1)}$$

Where:

- $CC_{Station\ "n"}$ is the overall value of CC indicator at the *n-th* station;
- $CC_{Material}$ is the value of CC indicator at the *n-th* station for the *Material* category of the classified I/O flows;
- CC_{Fossil} is the value of CC indicator at the *n-th* station for the *Fossil* category of the classified I/O flows;
- $CC_{Utility}$ is the value of CC indicator at the *n-th* station for the *Utility* category of the classified I/O flows;
- CC_{Other} is the value of CC indicator at the *n-th* station for the *Other* category of the classified I/O flows;
- $CC_{Emission}$ is the value of CC indicator at the *n-th* station for the *Emission* category of the classified I/O flows;
- CC_{Waste} is the value of CC indicator at the *n-th* station for the *Waste* category of the classified I/O flows.

Each item of equation 1 is calculated by multiplying the measured value of each flow (direct measurement of flow by using embedded sensors) with the specific unitary environmental impact (*LCA DB*). For example, the calculation of the Climate Change indicator for the *Material* category is reported in Equation 2.

$$CC_{Material} = \sum_{i=1}^{m} M\_q.ty_i * CC_i \qquad \text{(Equation 2)}$$

Where:

- $M\_q.ty_i$ is the quantity of the *i-th* material (*m* materials in total) measured at a specific "process station";
- CC_i is the unitary environmental impact of the *i-th* material (derived from *LCA DB*).

The arithmetic sum of each contribution represents the final environmental impacts of each process. The overall plant impact can be finally obtained considering the contributions of each process directly (e.g., manufacturing of components) or indirectly (e.g., waste management processes, office activities) needed for the plant life.

Concerning the economic KPI, the cost indicator is calculated as a sum of cash flows to each process station. Equation 3 was developed for this purpose, and it is used to calculate the cost indicator for a generic station "n".

$$Cost_{Station\ "n"} = Cost_{Material} + Cost_{Fossil} + Cost_{Utility} + Cost_{Other} + Cost_{Waste} \qquad \text{(Equation 3)}$$

Where:

- $Cost_{Station\ "n"}$ is the overall value of the cost indicator at the *n-th* station;
- $Cost_{Material}$ is the cost of the *Material* category items (classified in the I/O flows) at the *n-th* station;
- $Cost_{Fossil}$ is the cost of the *Fossil* category items (classified in the I/O flows) at the *n-th* station;
- $Cost_{Utility}$ is the cost of the *Utility* category items (classified in the I/O flows) at the *n-th* station;
- $Cost_{Other}$ is the cost of the *Other* category items (classified in the I/O flows) at the *n-th* station;
- $Cost_{Waste}$ is the cost of managing *Waste* category items (classified in the I/O flows) at the *n-th* station.

In this case, the cost items related to the *Emissions* category are not accounted for because there is no direct cost associated with the air or liquid emissions. The only cost item directly associated with these flows is the financial penalty that a company can get because they are over the emission thresholds imposed by national regulations. In this model, the framework was built assuming that these thresholds are never exceeded.

Again, as for environmental KPIs, each item of equation 3 is calculated by multiplying the measured value of each flow (direct measurement of flow by using embedded sensors) with the specific unitary cost impact (from *COST DB*), as described in equation 4.

$$Cost_{material} = \sum_{i=1}^{m} M\_q.ty_i * Cost_i \qquad \text{(Equation 4)}$$

Where:

- $M\_q.ty_i$ is the quantity of the *i-th* material (scraps for the Raw materials item and consumed materials for all the other items) measured at a particular "process station";
- $Cost_i$ is the unitary cost of the *i-th* material (derived from *COST DB*).

The outputs of the *Data processing* module are:

- The quantitative assessment of environmental, economic and resource consumption KPIs for each "process station";
- The graphical representation of the sustainable KPIs for identifying critical areas/assets (picture of the current production scenario for each KPI).

3.2.3 Results post-processing

The *results post-processing* phase manages results from the data processing module to identify sustainable manufacturing scenarios that minimise one or more KPIs previously defined. It is possible to solve the optimisation problem by combining production sets and determining the sustainable production schedule. The model for the combination of production sets is based on a combinatorial analysis that allows finding a problem solution by choosing and arranging the elements of finite sets (i.e., the production sets) following prescribed rules (i.e., the production target). Each rule defines a method of constructing some configuration of elements of the given set, called a combinatorial configuration. In this work, the optimisation problem is based on the production target, a crucial parameter for a discrete manufacturing system. Optimisation establishes the targeted number of products that need to be produced in a given timeframe (i.e., per hour, per shift, per day, per week, per month, per year, etc.). The possibility of scaling the optimization problem by following different timeframes allows fitting the framework with many application contexts to comply with the plant features, the type of product, the lot size, and the plant management requirements.

Before proceeding with the result post-processing explanation, three definitions are necessary:

- *Production target (Pta)*: target defined by the plant manager in terms of the number of products produced in a given period (i.e., per hour, per shift, per day, per week, per month, per year, etc.).
- *Production set (Pse)*: plant capability (production features) in a given configuration.
- *Production scenario (Psc)*: combination (mix) of production sets that allows reaching a production target.

The optimised production scenario is the main outcome of the proposed method. It is based on the combination of different production sets that minimise one or more KPIs. At least three baseline production sets are required to perform the mathematical optimisation problem: *no production* (the plant is running without production), *minimum capacity* (the plant is running at the lowest level of production), and *over-load capacity* (the plant is running at the highest level of production). These three baseline production sets are the initial input of the optimization process. Baseline production sets can be updated over time based on the new data collected, considering improvements and changes within the plant's boundaries. Besides, whenever a new production set is available (i.e., new data is collected for a given target), this one can be used as a new input to increase the number of sets for solving the optimization problem. The type of information necessary to define a production set must be discretized based on the production target (i.e., number of products per hour, per shift, per day, per week, per month, or per year). Thus, a production set can be mathematically defined as a vector composed of a set of parameters as reported in equation 5.

$$Pse_k = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_z \\ \vdots \\ X_M \end{bmatrix} \qquad \text{(Equation 5)}$$

Where:

- *Pse_k* is the *k-th* production set with $\begin{cases} k = integer\ (1, \dots, N) \\ N \geq 3 \end{cases}$
- *X_z* is the *z-th* parameter necessary to characterize the *k-th* production set with $\begin{cases} z = integer\ (1, \dots, M) \\ M \geq 5 \end{cases}$.

When the number of production sets (N) is equal to three, only baseline production sets are used. Otherwise, when N is higher than three, then baseline production sets and other known sets are used. The minimum set of parameters (M) required for solving the optimisation problem in each production set is five. Four mandatory parameters refer to the production (X1, X2, X3, and X4), and at least one parameter refers to the primary KPIs (from X5 to X8). If additional KPIs (both primary and secondary) need to be integrated within the optimization problem, they can be added as new parameters. However, when information for other flows is available (i.e., chemicals, gases), they can be used as additional parameters. The list of parameters is reported in Table 4.

Table 4. The list of parameters required for defining a production set

Parameter class	Label	Information type	Unit of measurement
Production parameters	X1	Working shifts	[#]
	X2	Working time	[h/day]
	X3	Working days	[days/discretization period*]
	X4	Pieces produced	[pcs/discretization period*]
Primary KPIs parameters	X5	Electricity consumed	[kWh/discretization period*]
	X6	Methane consumed	[m3/discretization period*]
	X7	Water consumed	[litre/discretization period*]
	X8	Lubricant consumed	[kg/discretization period*]
Secondary KPIs parameters	X9	Climate change (GWP)	[kg CO2 eq/discretization period*]
	X10	Ozone depletion (ODP)	[kg CFC-11 eq/discretization period*]
	X11	Terrestrial acidification (TAP)	[kg SO2 eq/discretization period*]
	X12	Freshwater eutrophication (FEP)	[kg P eq/discretization period*]
	X13	Particulate matter formation (PMF)	[kg PM10 eq/discretization period*]
	X14	Cumulative Energy Demand – Non-renewable (NRE)	[MJ/discretization period*]
	X15	Production cost	[k€/discretization period*]
Additional parameters	⋮	⋮	⋮
	X_M	Others	based on flow type

*Discretization period is based on the definition of production target (i.e., hour, shift, day, week, month, years, etc.)

It is worth noting that additional data is required for some specific production sets. For example, in the over-load capacity, the maximum number of days in overload capacity [days/ discretization period] is necessary, as well as the maximum number of days without production [days/ discretization period] is required for the no-production scenario. These constraints are based on different reasons. For example, the maximum number of days in overload capacity deals with the maximum working hours per week that a blue-collar can do based on national law (i.e., worker rights). If the company plans an employment downsizing or expansion, this constraint can be revised. The same goes for the maximum number of days without production, which is characterized by the terms established by national law concerning the lay-off (i.e., national collective agreement). Usually, this kind of data is available as company knowledge based on production simulations or data time series analysis. In both cases, the information for the mentioned boundary production scenarios is used to assess the KPIs in each process station.

As stated above, the optimisation process is based on the production target, which can be discretized based on different timeframes for discrete manufacturing systems. This option is of great interest to encompass many industrial fields in discrete manufacturing for a different level of granularity based on time discretization. The kernel of the optimisation tool is based on the combinatorial analysis of varying production sets (*Pse*), as reported in equation 6. Function (*f*) used to assess feasible production scenarios (*Psc_w*) includes the constraint of discretization period (i.e., the considered timeframe) and specific constraints of each production scenario (i.e., the maximum timeframe in overload capacity and the maximum timeframe without production).

$$Psc_w = f(Pse_1, \dots, Pse_k) \qquad \text{(Equation 6)}$$

Where:

- Psc_w is the *w-th* feasible production scenario $\begin{cases} w = integer\ (0, \dots, P) \\ P = \ 0\ (\text{no solution}) \\ P \ \geq \ 1\ (\text{exist at least one solution}) \end{cases}$

Feasible scenarios (*Psc_w*) are pointed out as a combination of production sets (combinatorial analysis) and that satisfy the following equation 7.

$$Pta \ \leq \ T_f \ \leq \ Pta + X\% \qquad \text{(Equation 7)}$$

Where:

- *Pta* is the production target defined by the end-user (plant manager).
- T_f is the number of pieces produced in a given timeframe for a feasible production scenario (*Psc_w*).
- *X%* is the tolerance defined by the end-user (plant manager). This percentage of variation is not fixed and can be decided at the beginning of the analysis based on the company's specific requirements.

The optimised scenario (*Psc_optimized*) is then assessed following the minimisation of a specific KPI (equation 8).

$$Psc_{optimized} \in \{Psc_w\} = \text{minimize} \ \ (KPI_i) \qquad \text{(Equation 8)}$$

Where:

- *Psc_optimized* is one of the *w-th* feasible production scenarios previously identified.
- KPI_i is the indicator selected for the optimisation problem.

Moreover, it is possible to solve the optimisation problem considering the combination of different parameters with an MCDM approach. Weights and scores for each attribute (KPI) need to be characterised based on the requirements of each manufacturing company. Supposing that multiple KPIs need to be accounted for the definition of the optimised production scenario, mathematical models can be adopted as a solver for the multi-objective problem. MCDM theories have been used to develop several approaches and tools to support the choices and strategies of designers and manufacturers (Hwang and Yoon 1981) (Marler and Arora 2004). One of the most well-known methods developed based on MCDM theory is the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Y.-J. Wang and Lee 2007). According to this method, the different production scenarios can be ranked considering the scores and weights provided to the KPIs. The TOPSIS method is not time-consuming due to easy implementation in a typical spreadsheet or dedicated software. Inputs required are only: (i) KPI weights (based on company targets and requirements towards sustainability), and (ii) scores for each production scenario concerning the selected KPIs. Once a new production scenario (including measured data) is available, it can be stored in the system repository and used for further analysis.

The post-processing analysis represents a helpful tool for companies towards implementing sustainable manufacturing principles, including zero-waste, responsible consumption of raw materials, minimization of air emissions, optimisation of process parameters and infrastructure management. If a manufacturing company defines an internal sustainability policy, the processing of numerical results for costs, resource consumptions and environmental impacts is a necessary step to implement corrective actions and to identify the most suitable manufacturing scheduling.

The outputs of the *Results post-processing* module are:

- The assessment of feasible production scenarios based on the production target and boundary production scenarios.

- The identification of an optimised scenario that minimises a defined KPI.
- The identification of the most sustainable scenario that minimises a set of KPIs.
- The identification of critical areas/assets that can be improved to reach better performance in the most sustainable scenario.

4 Case study

A case study has been conducted to test the potentialities and usefulness of the proposed approach in supporting industrial companies towards the multi-criteria optimisation of their production activities (environmental sustainability vs production cost vs resource consumption). The involved factory (a global leader in household production), located in Italy, produces washing machines/washer-dryers (WM/WD). The WM/WD plant is an actual example of a discrete multi-product manufacturing system, including in-house production processes (manual and automatic), manual assembly lines, testing laboratories, warehouses, and ancillary systems for managing semi-finished parts by external supply chain partners. The analysed plant has been recently modernised by implementing different I4.0 compliant technologies. Networks of sensors/IoT devices have been adopted for the production traceability and the real-time monitoring of relevant parameters (e.g., electricity consumption, lead time, number of faulty parts) in some production areas. Besides, the variability of the production mix is very high due to the inconstancy of market requirements (more than 50 models and platforms of WM/WD are jointly produced in the same production lines). For all the reasons mentioned above, the company needs to assess and optimise the production plant sustainability (environmental and economic), considering the production mix and production set.

4.1 System modelling and ICT infrastructure

The system modelling consisted of discretising the analysed process (i.e., subdivision in sub-phases), then characterising I/O flows for each machine/asset operating in each area of the plant. The plant discretisation, carried out according to the framework described in section 3.2.1, has been done involving the plant manager. The discretisation considered the arrangement of machines and the flow of components from the beginning (stamping and bending of the WM/WD cabinet and drum) to the end (product warehouse and shipment).

The general layout of the plant, including the production areas, is depicted in Figure 6. Starting from the production of the main components (external cabinet in area 1, drum and tank group in area 2), the WM/WD are then assembled in the six (plus one for reprocessing purposes) manual lines (area 3) by adding other components/functional groups (e.g., electric motor, pump, gaskets) stored in the component warehouse (area 4). The following testing lab (area 5) and packaging (area 6) allow finalising the products before the final warehouse and shipment (area 7). Area 8 is an auxiliary area responsible for generating and distributing compressed air. It must be said that two other auxiliary areas, the water purifier and waste management, are included in the plant. Still, they have not been considered in the subsequent analyses due to the impossibility of collecting a complete and reliable data set. However, such excluded areas can be analysed and managed as the compressor area since they are "services" for operating the other manufacturing areas.

1	1a	Cabinet Line
	1b	Front panel Line
	1’	Cabinet Painting Area
2	2a	Drum Line (old)
	2b	Drum Line (new)
	2’	Drum+Tank Line
3		Manual Assembly (6 + 1 parallel lines)
4		Component Warehouse
5		Testing Lab
6		Packaging
7		Finished Product Warehouse
8		Compressor Area

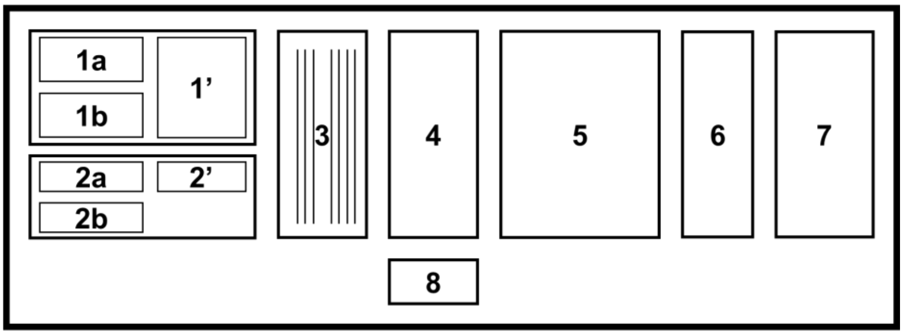

Figure 6. WM/WD manufacturing plant layout.

The I/O flows have been collected for the different machines and assets of the plant by using various sources. More specifically, the data belongs to four different typologies:

- *Measured*: these are the data measured through real-time acquisitions of an ICT infrastructure (e.g., sensors, IoT devices). Generally, such data are relative to single pieces/operations;
- *Estimated*: these are the data indirectly derived from aggregated information (e.g., data derived from company data management systems, aggregated measurements relative to entire lines or the entire plant, estimations based on machine plates and manuals) through an allocation per production volume;
- *Not considered*: these are the flows not considered in the present case study due to the unavailability of sufficiently reliable measured or estimated data;
- *Not applicable (N/A)*: these flows are not relevant to the specific area.

Table 5 shows the details about the means and tools used to collect data for the eight considered production areas.

Table 5. Details about the means/tools used for data collection

		Production areas											
		1a	**1b**	**1’**	**2a**	**2b**	**2’**	**3**	**4**	**5**	**6**	**7**	**8**
I/O Flows	**Raw Materials (I)**	Estimated from product design data (e.g. bill of materials, 3D models) or daily quantity of scraps	Estimated from product design data (e.g. bill of materials, 3D models) or daily quantity of scraps	N/A	Estimated from product design data (e.g. bill of materials, 3D models) or daily quantity of scraps	Estimated from product design data (e.g. bill of materials, 3D models) or daily quantity of scraps	Estimated from the daily quantity of scraps	Estimated from the daily quantity of scraps	N/A	N/A	Estimated from the daily quantity of scraps	N/A	N/A
	Pure Materials (I)	N/A	N/A	Estimated from monthly consumption	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Chemical Agents (I)	N/A	N/A	Estimated from monthly consumption	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Gases (I)	Measured by a flow meter	Measured by a flow meter	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Fuels (I)	N/A	N/A	Measured by a flow meter	N/A	N/A	N/A	N/A	N/A	N/A	Measured by a flow meter	N/A	N/A
	Air (I)	Measured by a flow meter	Measured by a flow meter	N/A	Estimated from machine rated consumption	Measured by a flow meter	Measured by a flow meter	Measured by a flow meter	N/A	N/A	N/A	N/A	N/A
	Electricity (I)	Measured by a power meter	Measured by a power meter	N/A	Estimated from monthly consumption	Measured by a power meter	Measured by a power meter	Measured by a power meter	Estimated from monthly consumption	Measured by a power meter	Measured by a power meter	Estimated from monthly consumption	Measured by a power meter
	Water (I)	N/A	N/A	Measured by a flow meter	N/A	N/A	N/A	N/A	N/A	Measured by a flow meter	N/A	N/A	N/A
	Maintenance (I)	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan	Maintenance plan
	Transport (I)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Estimated from the monthly consumption	N/A	N/A	Estimated from the monthly consumption	N/A
	Air emission (O)	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered
	Liquid emission (O)	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered
	Industrial waste (O)	Estimated from the daily quantity of waste	Estimated from the daily quantity of waste	Estimated from the daily quantity of waste	Estimated from the daily quantity of waste	Estimated from the daily quantity of waste	Estimated from the daily quantity of waste	Estimated from the daily quantity of waste	Estimated from the monthly quantity of waste	N/A	Estimated from the monthly quantity of waste	Estimated from the monthly quantity of waste	N/A

An example of the discretisation and characterisation for the Cabinet and Front panel Lines (1a and 1b) and Packaging area (6) is provided in Figure 7 A and B, respectively. The data reported are related to a production rate of 6400 WM/WD each day.

Table 6 shows how the available data (i.e., measurements or aggregated data) have been allocated to the considered production rate.

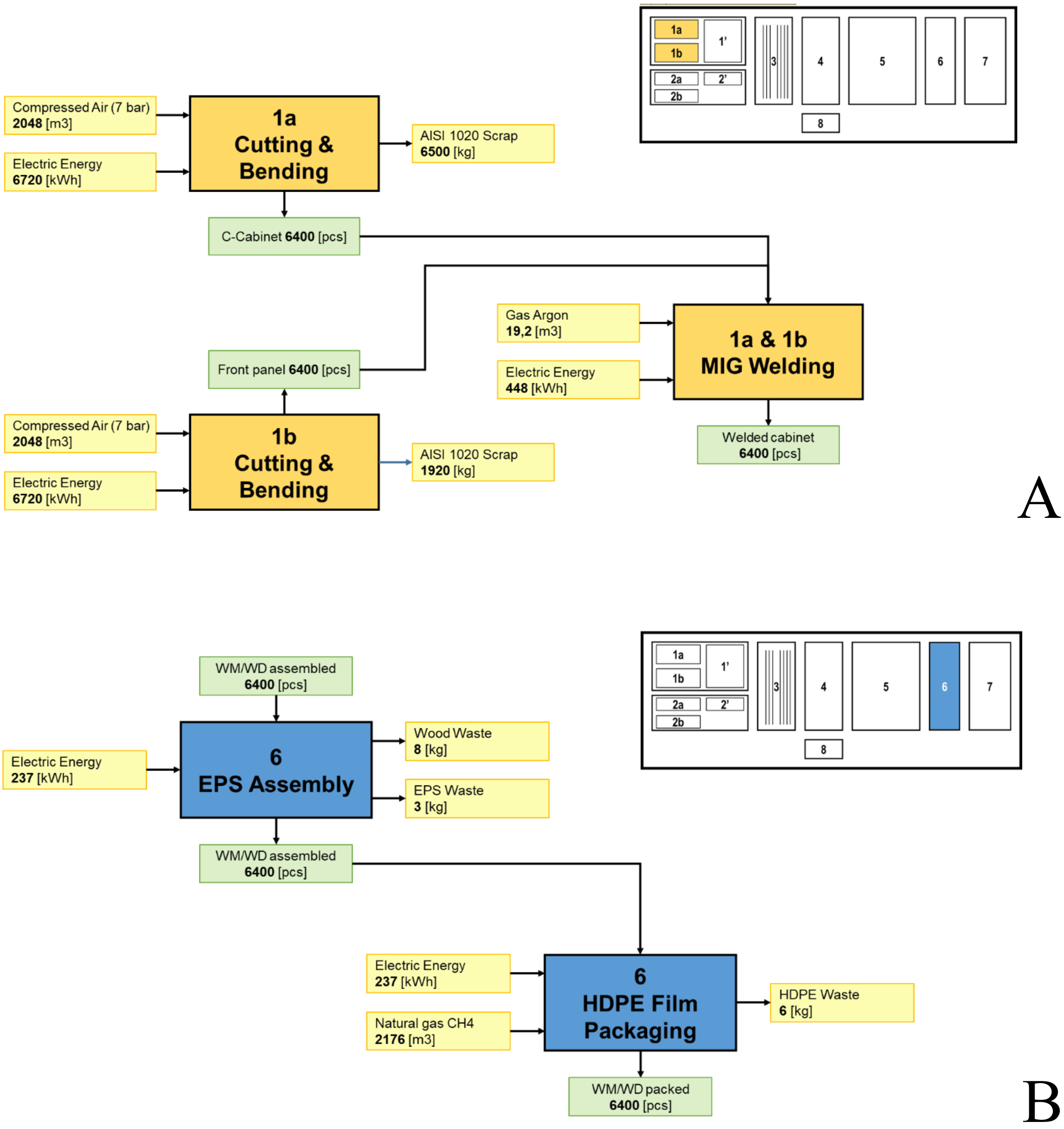

Figure 7. I/O analysis for the cabinet (n° 1a) and front panel (n° 1b) lines (A) and the packaging (n° 6) area (B).

Table 6. Allocation of measured or aggregated data to the production rate (6400 [pcs/day])

Manufacturing Area	Manufacturing Station	I/O Flow	Available Data	Derived Data
1	1a – Cutting and Bending (Cabinet)	Compressed Air	0.32 [m^3/pc] (measured)	0.32 [m^3/pc] * 6400 [pcs] = 2048 [m^3]
		Electric Energy	1.05 [kWh/pc] (measured)	1.05 [kWh/pc] * 6400 [pcs] = 6720 [kWh]
		Material Scrap (Steel AISI 1020)	Finished Cabinet = 8.6 [kg/pc] (estimated from Cabinet 3D model) Sheet metal coil = 9.72 [kg/pc] (derived from bill of materials)	(9.72 [kg/pc] – 8.6 [kg/pc]) * 6400 [pcs] = 6500 [kg]
	1b – Cutting and Bending (Front panel)	Compressed Air	0.32 [m^3/pc] (measured)	0.32 [m^3/pc] * 6400 [pcs] = 2048 [m^3]
		Electric Energy	1.05 [kWh/pc] (measured)	1.05 [kWh/pc] * 6400 [pcs] = 6720 [kWh]
		Material Scrap (Steel AISI 1020)	Finished Front panel = 2.48 [kg/pc] (estimated from Front panel 3D model) Sheet metal coil = 2.78 [kg/pc] (derived from bill of materials)	(2.78 [kg/pc] – 2.48 [kg/pc]) * 6400 [pcs] = 1920 [kg]
	1a & 1b – MIG Welding	Gas (Argon)	0.003 [m^3/pc] (measured)	0.03 [m^3/pc] * 6400 [pcs] = 19.2 [m^3]
		Electric Energy	0.07 [kWh/pc] (measured)	0.07 [kWh/pc] * 6400 [pcs] = 448 [kWh]
6	6 – EPS Assembly	Electric Energy	0.037 [kWh/pc] (measured)	0.037 [kWh/pc] * 6400 [pcs] = 237 [kWh]
		Industrial Waste (Wood)	≈ 170 [kg/month] (estimated monthly quantity of waste)	≈ 170 [kg/month] / 134400 [pcs/month] * 6400 [pcs] ≈ 8 [kg]
		Industrial Waste (EPS)	≈ 65 [kg/month] (estimated monthly quantity of waste)	≈ 65 [kg/month] / 134400 [pcs/month] * 6400 [pcs] ≈ 3 [kg]
	6 – HDPE Film Packaging	Electric Energy	0.037 [kWh/pc] (measured)	0.037 [kWh/pc] * 6400 [pcs] = 237 [kWh]
		Fossil Fuel (Natural Gas CH_4)	0.34 [m^3/pc] (measured)	0.34 [m^3/pc] * 6400 [pcs] = 2176 [m^3]
		Industrial Waste (HDPE)	≈ 125 [kg/month] (estimated monthly quantity of waste)	≈ 125 [kg/month] / 134400 [pcs/month] * 6400 [pcs] ≈ 6 [kg]

4.2 Data processing

The *Data processing* step allows to point out an overall picture of the factory sustainability. Specifically, for this case study, the following repositories have been adopted as a source of secondary data:

- Ecoinvent 3.1 as *LCA DB*;
- In-house cost repository (part of the product lifecycle management system) as *COST DB*.

An Excel-based tool has been realised to perform all the calculations needed for data processing (i.e., KPIs assessment) and post-processing (i.e., optimisation), according to the proposed mathematical model previously described through equations 1 – 8. For example, Table 7 reports the results obtained by evaluating the complete set of KPIs for the eight production areas considered in the case study. Figure 8, instead, shows another way to represent the KPIs by using a graphical representation through colour maps. In both cases, the analysed production set refers to one day of production at *standard capacity* (1.300.000 [pcs/year], which corresponds to 6400 [pcs/day]).

Table 7. KPI analysis for one day of production at standard capacity (6400 WM/WD per day)

KPI		Total	1. Cabinet	2. Drum+Tank	3. Assembly	4. Component Warehouse	5. Testing	6. Packaging	7. Finished Product Warehouse	8. Compressors
Resource	**Electricity [kWh]**	4.96E+04	1.27E+04	1.31E+04	2.35E+03	4.70E+02	6.44E+03	1.17E+02	3.52E+02	1.41E+04
	Natural Gas [m^3]	5.91E+03	5.65E+03	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.61E+02	0.00E+00	0.00E+00
	Water [l]	5.41E+05	3.13E+04	0.00E+00	0.00E+00	0.00E+00	5.09E+05	0.00E+00	0.00E+00	0.00E+00
	Lubricant [kg]	2.95E+00	2.46E+00	4.92E-01	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
Economic	**Cost [€]**	20959.42	9464.11	4445.39	633.87	126.77	2278.35	112.62	95.08	3803.22
Environmental	**CC [kgCO$_2$eq.]**	3.94E+04	1.42E+04	9.96E+03	1.49E+03	2.97E+02	4.08E+03	2.50E+02	2.22E+02	8.91E+03
	TAP [kgSO2eq.]	1.78E+02	7.15E+01	4.52E+01	5.91E+00	1.18E+00	1.62E+01	1.39E+00	8.80E-01	3.53E+01
	FEP [kgPeq.]	9.85E+00	4.83E+00	2.21E+00	2.80E-01	6.00E-02	7.50E-01	5.00E-02	4.00E-02	1.63E+00
	PMF [kgPM10eq.]	6.42E+01	2.41E+01	2.08E+01	1.87E+00	3.70E-01	5.15E+00	4.50E-01	2.80E-01	1.12E+01
	CED-NRE [MJ]	2.67E+02	1.34E+02	5.19E+01	7.66E+00	1.53E+00	2.09E+01	3.83E+00	1.14E+00	4.58E+01

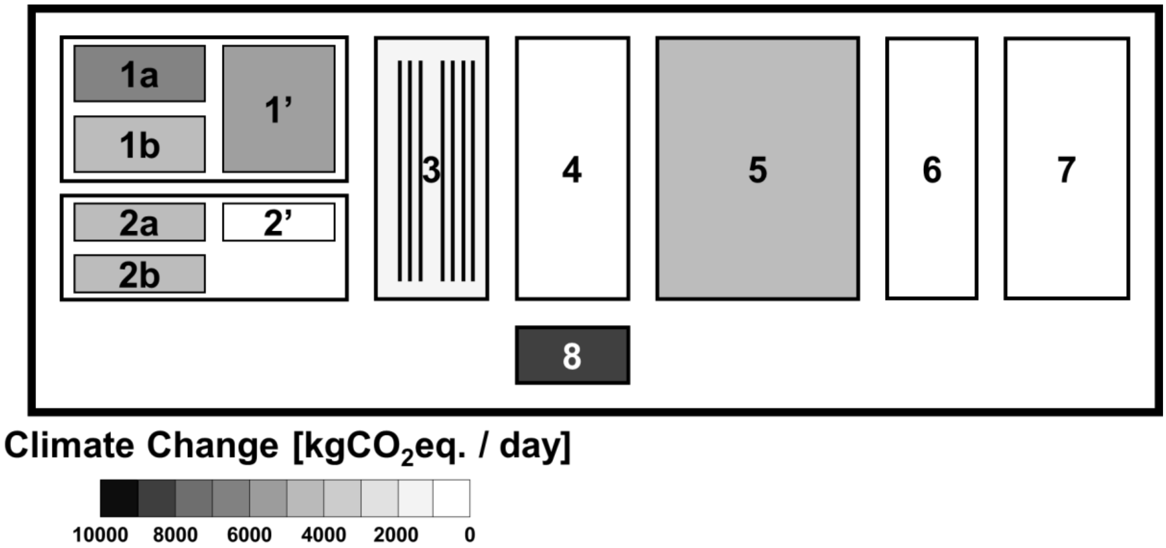

Figure 8: Colour map representation of the plant for Climate Change KPI (environmental).

Concerning the electricity consumption indicator, the most critical area highlighted in this production scenario is the *Compressor* area (area 8), which requires massive quantities of energy to produce and distribute the compressed air needed in the whole plant. However, also the *Cabinet* area (area 1) (particularly sub-area 1a) and *Drum+Tank* area (area 2) are energy-intensive areas due to the presence of high-tonnage presses for sheet metal cutting/bending. As expected, natural gas is mainly consumed during the painting phase (particularly sub-area 1' of the *Cabinet* area). Simultaneously, a small fraction is required for finished product *Packaging* (heating of the plastic shrink-wrap). Water is almost wholly consumed during the *Testing* phase when all the WM/WD are tested in different operating conditions (e.g., washing, spin-dryer, water heating) according to relevant standards.

Concerning the Climate Change indicator, the most critical areas highlighted in this production scenario is the *Cabinet* area (area 1), followed by the *Drum+Tank* area (area 2) and the *Compressor* area (area 8). Similar conclusions can also be derived by analysing the other environmental KPIs.

Also, concerning the cost indicator, the most critical area highlighted in this production scenario is the *Cabinet* area (area 1), accounting for about 50% of the total cost. This value is a consequence of three main flows: (i) materials (e.g., steel scraps, chemicals for degreasing and painting), (ii) consumption of natural gas for cleaning and painting (sub-area 1'), and (iii) consumption of electricity for sheet metal stamping. The exact reasons are behind the high costs of the *Drum+Tank* area (area 2). In contrast, the high consumption of electric energy influences the costs of areas *Compressor* (area 8) and *Testing* (area 5).

By profoundly analysing such results and identifying the most critical areas and flows, the most suitable remedial actions (e.g., improved plant management) and alternative technologies (e.g., more efficient machines) can be implemented to reduce the environmental/economic impacts and improve the overall plant sustainability.

It is worth noting that, results reported in Table 7 are deterministic, and their uncertainty is not reported. However, results, particularly the ones referring to secondary KPIs, are affected by uncertainty. Uncertainty can be divided into two types which are epistemic and aleatory. Epistemic uncertainty derives from the lack of knowledge of a parameter, phenomenon or process. In contrast, aleatory uncertainty is caused by probabilistic variations in a random event. In the proposed example, epistemic uncertainty deals with the environmental and cost data quality (i.e., background data). The uncertainty concerns how the data were collected (i.e., the use of pedigree matrix for LCA datasets and the historical data company for unitary cost) and their variability over time. In addition, the LCA model (i.e., the ReCiPe method) is empirical, and it is affected by uncertainty as well. On the other hand, the data retrieved from I/O flows and primary KPIs are less sensitive to epistemic uncertainty since they are directly measured. Sensitivity analysis and statistical considerations are recommended before proceeding with the result post-processing.

4.3 Result post-processing

The post-processing phase starts with defining new target scenarios, including production rates and product models, based on external requirements. In this case study, the new production target (*Pta*) only regards the number of WM/WD produced in 1 year. According to the indications of the involved company, the *Pta* has been set to 920000 [pcs/year]. This target is lower than the *standard capacity* considered, as shown in the previous section (1300000 [pcs/year]). Thus, an optimisation analysis is required for the right plant's management toward economic and environmental sustainability.

The company has also established some different production sets. A combinatorial analysis has been performed to find the combinations that produce the correct number of pieces defined by the established target (i.e., 920000 [pcs/year]), minimising KPIs.

According to company constraints, four production sets (*Pse_1 - standard capacity*, *Pse_2 - over-load capacity*, *Pse_3 - minimum capacity* and *Pse_4 - no-production*) have been used as initial baselines of the optimisation problem. The needed data for each non-standard production set has been estimated based on historical data. Aggregated data are reported in the following Table 8. It is important to note that the chosen discretization period for the optimisation problem is the month. This choice is justified because the production volumes can vary for the analysed plant with a minimum time horizon of 1 month (at least). Concerning constraints in the optimization problem, *over-load capacity* and *no production* sets can be kept only for a limited number of months due to external issues not linked with the production itself (worker conditions, health, and social regulations).

Table 8. Details about the four production sets (Pse) used as input for the optimisation problem

Parameters	**Label**	**Pse_1 Standard**	**Pse_2 Over-load**	**Pse_3 Minimum**	**Pse_4 No production**
Working shifts [#]	X1	2	3	1	0
Working time [h/day]	X2	14	18	8	0
Working days [day/year]	X3	220	220	220	0
Production volume [pcs/year]	X4	1300000	1700000	400000	0
Electricity consumption [kWh/month]	X5	910000	1133333	416667	50000
Natural gas consumption [m3/month]	X6	108333	130333	55000	3000
Water consumption [l/month]	X7	9909741	13001983	3092241	90000
Lubricant consumption [kg/month]	X8	54	67	17	0
Constraints					
Maximum N° of months for this scenario [month/year]	N/A	12	4	12	2

4.3.1 Production schedule optimisation

The abovementioned constraints, together with the production target and the other relevant parameters about I/O flows, have been considered during the assessment of production scenarios. Figure 9 reports seven different feasible production scenarios (*Psc*) able to reach the defined target, together with the evaluation of the four primary KPIs. Firstly, such indicators have been chosen because they are particularly interesting for the involved company. Secondly, the available input data needed for the primary KPIs analyses could be considered more statistically significant since derived from long-term monitoring. These considerations allowed obtaining more robust and reliable data. However, a similar analysis could be performed by considering the other environmental or economic indicators of the proposed method (Figure 2).

Scenario #	Production sets	Months #	Quantity [pcs/year]	Electricity [kWh/year]	Natural Gas [m3/year]	Water [l/year]	Lubricant [kg/year]
Psc_1	Standard	3	3.25E+05	2.73E+06	3.25E+05	2.97E+07	1.63E+02
	Over-load	3	4.25E+05	3.40E+06	3.91E+05	3.90E+07	2.00E+02
	Minimum	6	2.00E+05	2.50E+06	3.30E+05	1.86E+07	1.00E+02
	No production	0	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	TOTAL	12	9.50E+05	8.63E+06	1.05E+06	8.73E+07	4.63E+02
Psc_2	Standard	6	6.50E+05	5.46E+06	6.50E+05	5.95E+07	3.25E+02
	Over-load	1	1.42E+05	1.13E+06	1.30E+05	1.30E+07	6.67E+01
	Minimum	4	1.33E+05	1.67E+06	2.20E+05	1.24E+07	6.67E+01
	No production	1	0.00E+00	5.00E+04	3.00E+03	9.00E+04	0.00E+00
	TOTAL	12	9.25E+05	8.31E+06	1.00E+06	8.49E+07	4.58E+02
Psc_3	Standard	8	8.67E+05	7.28E+06	8.67E+05	7.93E+07	4.33E+02
	Over-load	0	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Minimum	2	6.67E+04	8.33E+05	1.10E+05	6.18E+06	3.33E+01
	No production	2	0.00E+00	1.00E+05	6.00E+03	1.80E+05	0.00E+00
	TOTAL	12	9.33E+05	8.21E+06	9.83E+05	8.56E+07	4.67E+02
Psc_4	Standard	2	2.17E+05	1.82E+06	2.17E+05	1.98E+07	1.08E+02
	Over-load	4	5.67E+05	4.53E+06	5.21E+05	5.20E+07	2.67E+02
	Minimum	5	1.67E+05	2.08E+06	2.75E+05	1.55E+07	8.33E+01
	No production	1	0.00E+00	5.00E+04	3.00E+03	9.00E+04	0.00E+00
	TOTAL	12	9.50E+05	8.49E+06	1.02E+06	8.74E+07	4.58E+02
Psc_5	Standard	6	6.50E+05	5.46E+06	6.50E+05	5.95E+07	3.25E+02
	Over-load	1	1.42E+05	1.13E+06	1.30E+05	1.30E+07	6.67E+01
	Minimum	5	1.67E+05	2.08E+06	2.75E+05	1.55E+07	8.33E+01
	No production	0	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	TOTAL	12	9.58E+05	8.68E+06	1.06E+06	8.79E+07	4.75E+02
Psc_6	Standard	5	5.42E+05	4.55E+06	5.42E+05	4.95E+07	2.71E+02
	Over-load	2	2.83E+05	2.27E+06	2.61E+05	2.60E+07	1.33E+02
	Minimum	3	1.00E+05	1.25E+06	1.65E+05	9.28E+06	5.00E+01
	No production	2	0.00E+00	1.00E+05	3.00E+03	1.80E+05	0.00E+00
	TOTAL	12	9.25E+05	8.17E+06	9.70E+05	8.50E+07	4.54E+02
Psc_7	Standard	7	7.58E+05	6.37E+06	7.58E+05	6.94E+07	3.79E+02
	Over-load	0	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Minimum	5	1.67E+05	2.08E+06	2.75E+05	1.55E+07	8.33E+01
	No production	0	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	TOTAL	12	9.25E+05	8.45E+06	1.03E+06	8.48E+07	4.63E+02

Figure 9: Example of KPIs assessment of different manufacturing scenarios considering a production target of 920000 [pcs/year].

The *Results post-processing* module allows finding the best production schedule to minimise each selected KPI (see coloured cells in Figure 9). As reported, production scenario #7 (*Psc_7*) can be considered the optimum in terms of water consumption. On the other hand, production scenario #6 (*Psc_6*) is the optimised one for electricity, natural gas, and lubricant consumption. This optimization can be considered the first run of the proposed methodology. Subsequently, when new data referring to novel production sets will be available, they can be integrated into the optimization problem. Thus, the optimal solution will not be static over time.

4.3.2 Multi-objective optimisation

The production schedule optimisation results can lead to the identification of different optimums. For example, Figure 9 highlights that if the Water indicator is considered the most important one, scenario #7 (*Psc_7*) should be chosen to minimise the WM/WD production impacts. If, instead, Electricity, Natural Gas or Lubricant are considered the most relevant KPIs, scenario #7 (*Psc_7*) is undoubtedly the preferable solution. Moreover, different optimums would probably have been found if the environmental and economic indicators had been analysed.

Such results suggest that choosing the most sustainable production schedule is not a trivial problem. Indeed, it requires a trade-off among the KPIs. Therefore, a multi-objective analysis could be carried out by applying one of the existing MCDM methods. In this case study, TOPSIS has been used to establish an optimised scenario according to the company objectives (Figure 9). TOPSIS is based on calculating the positive ideal solution (S1 with a normalised value of 1), which is the best score in each criterion, and the negative ideal solution (S2 with a normalised value of 0), which is the worst score in each criterion. The alternative that is finally chosen should have the shortest geometric distance from S1 and the longest geometric distance from S2 (Hwang and Yoon 1981) (Velasquez and Hester 2013). A normalisation procedure is usually required to make such evaluations because the different criteria are of incongruous dimensions. The calculation of distances requires to assign a weight (from 0 – not relevant to 10 – very important) to each criterion (i.e., each KPI) that in the present case study have been assigned according to the indications of the involved company:

- Water: 10
- Electricity: 7
- Natural Gas: 4
- Lubricant: 3

The very high importance attributed to the Water KPI is justified because the involved manufacturing company is located in a geographical area where water resource is scarce (i.e. plant far from water basins); thus, water supply and cost currently represent a primary issue. The second most important indicator is Electricity. The analysed industrial plant consumes high quantities of electric energy that, as previously demonstrated, represent the most critical flow from both the economic and environmental points of view in most production areas. Concerning Natural Gas, even if this resource is almost only used in the Cabinet Painting Area, its market fluctuations and the foreign dependence of the country where the analysed plant is located (i.e. Italy), lead to not negligible importance. Finally, Lubricant does not currently represent a critical flow for the involved manufacturing company. Thus the lowest weight has been assigned to this KPI.

Results obtained using TOPSIS, and considering the same seven production scenarios previously analysed, are reported in Figure 10. From this concurrent analysis of the four considered KPIs, scenario #6 (*Psc_6*) was the best alternative. It has the highest similarity with the positive ideal solution (i.e., 0.97 is the closest value to 1). Despite the increased weight assigned to the Water indicator, scenario #7 (*Psc_7*) was not the best option (0.55 of similarity). In contrast, surprising results can be observed for scenarios #2 (*Psc_2*) and #3 (*Psc_3*) (0.74 and 0.80 of similarity, respectively). These scenarios did not obtain optimum results for none of the KPIs (as shown in Figure 9) but jointly constitute “balanced” solutions that assure a high resource consumption sustainability. Such outcomes cannot be easily derived from a simple KPIs assessment and demonstrate the usefulness of the multi-objective analysis in the context of production schedule optimisation.

	SCENARIO #						
	Psc_1	Psc_2	Psc_3	Psc_4	Psc_5	Psc_6	Psc_7
	EVALUATION MATRIX						
Electricity [kWh]	8.63E+06	8.31E+06	8.21E+06	8.49E+06	8.68E+06	8.17E+06	8.45E+06
Natural gas [m^3]	1.05E+06	1.00E+06	9.83E+05	1.02E+06	1.06E+06	9.70E+05	1.03E+06
Water [l]	8.73E+07	8.49E+07	8.56E+07	8.74E+07	8.79E+07	8.50E+07	8.48E+07
Lubricant [kg]	4.63E+02	4.58E+02	4.67E+02	4.58E+02	4.75E+02	4.54E+02	4.63E+02
	NORMALISED EVALUATION MATRIX						
Electricity	3.87E-01	3.73E-01	3.69E-01	3.81E-01	3.89E-01	3.67E-01	3.79E-01
Natural gas	3.89E-01	3.73E-01	3.66E-01	3.78E-01	3.93E-01	3.61E-01	3.84E-01
Water	3.83E-01	3.73E-01	3.76E-01	3.83E-01	3.86E-01	3.73E-01	3.72E-01
Lubricant	3.78E-01	3.74E-01	3.81E-01	3.74E-01	3.88E-01	3.71E-01	3.78E-01
	WEIGHED NORMALISED EVALUATION MATRIX						
Electricity	2.71E+00	2.61E+00	2.58E+00	2.67E+00	2.73E+00	2.57E+00	2.66E+00
Natural gas	1.56E+00	1.49E+00	1.46E+00	1.51E+00	1.57E+00	1.44E+00	1.54E+00
Water	3.83E+00	3.73E+00	3.76E+00	3.83E+00	3.86E+00	3.73E+00	3.72E+00
Lubricant	1.13E+00	1.12E+00	1.14E+00	1.12E+00	1.16E+00	1.11E+00	1.13E+00
	POSITIVE IDEAL SOLUTION (S1)						
Electricity	2.18E-04	1.33E-02	2.12E-02	3.56E-03	0.00E+00	2.57E-02	4.95E-03
Natural gas	1.80E-04	5.99E-03	1.16E-02	3.37E-03	0.00E+00	1.59E-02	1.07E-03
Water	7.64E-04	1.73E-02	1.00E-02	5.61E-04	0.00E+00	1.63E-02	1.84E-02
Lubricant	9.39E-04	1.68E-03	4.14E-04	1.68E-03	0.00E+00	2.60E-03	9.39E-04
	4.58E-02	1.96E-01	2.08E-01	9.58E-02	0.00E+00	2.46E-01	1.59E-01
	NEGATIVE IDEAL SOLUTION (S2)						
Electricity	2.12E-02	2.02E-03	2.09E-04	1.01E-02	2.57E-02	0.00E+00	8.07E-03
Natural gas	1.27E-02	2.37E-03	3.41E-04	4.63E-03	1.59E-02	0.00E+00	8.71E-03
Water	1.16E-02	1.56E-05	1.26E-03	1.25E-02	1.84E-02	6.24E-05	0.00E+00
Lubricant	4.14E-04	1.01E-04	9.39E-04	1.01E-04	2.60E-03	0.00E+00	4.14E-04
	2.14E-01	6.71E-02	5.25E-02	1.65E-01	2.50E-01	7.90E-03	1.31E-01
	SIMILARITY CALCULATION						
S1	4.58E-02	1.96E-01	2.08E-01	9.58E-02	0.00E+00	2.46E-01	1.59E-01
S2	2.14E-01	6.71E-02	5.25E-02	1.65E-01	2.50E-01	7.90E-03	1.31E-01
S1+S2	2.60E-01	2.63E-01	2.60E-01	2.61E-01	2.50E-01	2.54E-01	2.90E-01
S1/(S1+S2)	***0.18***	***0.74***	***0.80***	***0.37***	***0.00***	***0.97***	***0.55***

Figure 10: Example of multi-objective optimisation considering a production target of 920.000 [pcs/year] and the four Resource consumption KPIs.

4.4 Discussion

The proposed case study and the results obtained open the discussion toward relevant implications both at the scientific and managerial/industrial levels. From the industrial point of view, the case study confirmed the applicability of the proposed method in authentic contexts and using available data from the production areas. Besides, the effectiveness in supporting companies in the analysis, identifying criticalities, and above all, the proper management of production plants has been demonstrated. More specifically, the method allows plant managers to consider sustainability issues and the other traditional drivers during the decision-making process before scheduling the production of a discrete manufacturing plant. This feature is essential, for instance, when a company intends to improve its sustainability performance. For example, the marketing department could require sustainability improvement (e.g., penetration of new markets with environmentally aware final users). Besides, the enhancement could be mandatory for respecting new legislations (e.g., new national or international directives) or even to satisfy requirements imposed by clients (e.g., in the case of a company acting as a supplier).

It is worth highlighting that the proposed method mainly focuses on the environmental and economic sustainability assessment and management of production plants. It is evident that the scheduling choices, in the context of complex production systems, require to consider many additional drivers and constraints, as management of human resources, warehouse stocks in case of over-loads periods, supervision of staff and plant systems in non-working months, quality of final products, production mix, legislations compliance, etc. Focusing on sustainability objectives potentially represents a limitation of the present study. However, the proposed framework should be viewed as a tool to be used by plant managers, combined with other management tools (e.g., enterprise resource planning, manufacturing execution system, supply chain management, energy management), to manage sustainability issues. These questions assume a leading role in the industrial sector due to ever more stringent legislations, action plans, and increasing pressure from the market.

Another relevant feature from the management point of view is the scalability of the method. It can be applied in production plants with different constraints (e.g., production target, production sets), features, available I/O flows, sources of data (e.g., real-time data, historical data), levels of granularity of the process mapping and by considering the most relevant indicators for the specific application. In the analysed plant, only resource consumption KPIs have been considered, but using the same approach and other economic and environmental KPIs could guide the choice of the best production scenario from different points of view. In this way, it is quite common to obtain conflicting results: the higher the number of considered indicators, the higher the possibility of getting more than one “local” optimal scenario. Therefore, a trade-off analysis must consider all these aspects and finally find an “absolute” optimal scenario. Also, the proposed method has proven to be effective to solve such management issue regarding this aspect. The integration of an MCDM method, while considering several relevant and concurrent drivers, could effectively support the decision-making process in the management of plants.

Concerning the scientific implications, the proposed method positively contributes to integrating the existing state of the art studies concerning the I4.0-related framework for the sustainability assessment of production systems. Current frameworks are mainly based on theoretical models (Enyoghasi and Badurdeen 2021). Thus, they do not indicate how to practically gather and elaborate needed data (real-time and historical data). Consequently, they do not discuss opportunities and limitations about the industrial application of such methods (Thiede et al. 2016; Saad, Nazzal, and Darras 2019). In this paper, instead, a structured framework to collect, manage, elaborate, and interpret data is presented. In the era of I4.0, the ability to use the massive amount of available information (commonly known as “big data”) could potentially represent a critical competitive factor towards the efficiency improvement of tasks for manufacturing companies. In this context, the I/O flows classification reported in Table 3 clearly illustrates how a process mapping should be conducted and which data need to be collected to monitor the sustainability of a plant. The implementation in the WM/WD plant case study demonstrated the applicability of the approach also in complex contexts (multi-product production systems, heterogeneous production processes, many different I/O flows, data gathered by using the available ICT infrastructure or estimated based on historical data stored in company repositories, etc.). The case study should foster other scholars in using this framework in other similar or heterogeneous industrial applications.

If, on one side, the possibility to effectively use and manage vast amounts of relevant production data can be certainly considered a strength of the proposed method, on the other side, the data availability is a limit that potentially reduces the applicability of this method in “dated” production plants. It is worth emphasising that real-time analyses can be only carried out if the production plant is equipped with a network of sensors/IoT devices, able to collect data about the relevant

I/O flows with the desired level of granularity. The more extensive the network of sensors is, the more the process mapping will be detailed and the obtained results significant. Otherwise, only historical or estimated data can be used. Results will be certainly less reliable and less helpful in supporting plant scheduling.

Finally, another essential outcome derived by this framework refers to the possibility to manage production activities based on feature outlook and contracts. This outcome will lead to a certified production in terms of environmental indicators towards the opportunity to perform an environmental product declaration (EPD) during the production stage or even early in the engineering design process.

5 Conclusions

The paper presented a framework for the sustainable management of smart manufacturing plants in the era of I4.0. It mainly consists of defining sustainability KPIs for the manufacturing plant, collecting and processing production-related data for evaluating KPIs, and determining an optimised production scenario through an MCDM approach. The case study explained the application of the proposed framework within a real company to assess the production plant's sustainability and identify the optimal production scenario. The framework can manage data different for their level of detail and can integrate MCDM methods for supporting the definition of the best production scenario under conflicting objectives.

Summarizing the outcomes, considering the results obtained with the case study, and comparing them with previous literature studies, it can be said that the proposed framework and the model for collecting data represent an appropriate step toward the effective integration of several topics that are usually treated separately: the I4.0 paradigm, process mapping tools (e.g. MFA), environmental sustainability assessment through LCA-based methods and indicators, economic evaluation of production systems, multi-criteria methods to concurrently consider different drivers, decision-making supporting tools for the optimized management of manufacturing plants.

As a future outlook, the framework robustness should be further investigated through its application in different industrial sectors. Developing a dedicated software tool could be essential to foster the framework application within the industry. Another aspect that deserves to be further investigated is undoubtedly the data and results uncertainty, which can be managed by integrating statistical analysis within the proposed framework, especially in the result post-processing phase. The framework here proposed only accounts for economic and environmental KPIs. The social pillar of sustainability should be considered in the future for providing stakeholders with a holistic representation of a production plant. As a future activity, it should be interesting to use these data to create simulation-based scenarios to assess KPIs of different equipment and machines to choose the most suitable ones for a given production set. Further investigations will also be dedicated to those models used to determine the best production planning and scheduling. It will allow moving from discrete timeframes (i.e., months, weeks) to real-time adaptation.

6 References

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