Master thesis

Sustainable Value Stream Mapping: Development of an Algorithm for the Identification of Sustainability Potentials within Value Streams

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under the supervision of

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Kurzfassung

Im Zuge internationaler Klimaschutzinitiativen wie dem Pariser Abkommen sowie dem European Green Deal wurden verbindliche Zielvorgaben zur Reduktion von Treibhausgasemissionen formuliert, die produzierende Unternehmen betreffen. Der Industriesektor war im Jahr 2023 für 20,3 % der gesamten Treibhausgasemissionen innerhalb der Europäischen Union verantwortlich und trägt damit maßgeblich zur Erderwärmung bei. Um irreversible ökologische, soziale und wirtschaftliche Schäden zu vermeiden, sind drastische Emissionsreduktionen erforderlich. Unternehmen stehen dabei vor der Herausforderung, ihre Produktionsprozesse nachhaltiger zu gestalten, ohne ihre Wettbewerbsfähigkeit zu verlieren oder das Wohlbefinden ihrer Mitarbeitenden zu vernachlässigen.

Mit wachsendem gesellschaftlichem Druck, verschärften regulatorischen Anforderungen sowie steigenden Erwartungen entlang der Lieferkette steigt die Relevanz, Nachhaltigkeitsaspekte in der industriellen Produktion systematisch zu erfassen und zu bewerten. Da die Umsetzung dieser Anforderungen eine nachvollziehbare Herleitung und kontinuierliche Verbesserung ökologischer und sozialer Wirkungen in operativen Prozessen voraussetzt, gewinnen automatisierte Ansätze zur Identifikation von Nachhaltigkeitspotenzialen in Wertströmen zunehmend an Bedeutung.

Ein bewährter Ansatz zur Prozessoptimierung ist das Lean-Management-Werkzeug Value Stream Mapping (VSM). Durch die Erweiterung des klassischen VSM um ökologische und soziale Nachhaltigkeitskennzahlen entsteht ein methodisches Instrument zur ganzheitlichen Bewertung von Produktionsprozessen entlang der drei Säulen der Nachhaltigkeit. Gleichzeitig bieten digitale Technologien im Kontext von Industrie 4.0 neue Möglichkeiten, Produktionsdaten automatisiert auszuwerten und Entscheidungshilfen datenbasiert zu gestalten.

Ziel dieser Arbeit ist die Entwicklung eines Algorithmus zur automatisierten Identifikation und Bewertung von Nachhaltigkeitspotenzialen in industriellen Wertströmen. Hierzu werden bestehende Ansätze und Werkzeuge zur Berücksichtigung von Nachhaltigkeitsaspekten in Produktionssystemen analysiert. Der entwickelte Algorithmus kombiniert etablierte Entscheidungsunterstützungsverfahren mit produktionstechnischen Kennzahlen und nutzt digitale Strukturen zur systematischen Bewertung von Nachhaltigkeitspotenzialen. Die Anwendung richtet sich insbesondere an produzierende Unternehmen, die klassische Lean-Methoden um Nachhaltigkeitsaspekte erweitern und datenbasiert Handlungsfelder identifizieren möchten. Die Praxistauglichkeit und Wirksamkeit des entwickelten Algorithmus wird abschließend anhand eines realen industriellen Fallbeispiels validiert und diskutiert.

Abstract

International climate protection initiatives, including the Paris Agreement and the European Green Deal, have established binding targets for reducing greenhouse gas emissions that directly impact manufacturing companies. The industrial sector was responsible for 20.3% of the total greenhouse gas emissions within the European Union in 2023 and thus contributes significantly to global warming. To avoid irreversible ecological, social, and economic damages, drastic emission reductions are required. Companies face the challenge of making their production processes more sustainable without losing their competitiveness or neglecting the well-being of their employees.

With increasing societal pressure, tightened regulatory requirements, and rising expectations along the supply chain, the relevance of systematically identifying and evaluating sustainability aspects in industrial production is growing. Since the implementation of these requirements presupposes a comprehensible derivation and continuous improvement of ecological and social impacts in operational processes, automated approaches to identifying sustainability potentials in value streams are becoming increasingly important.

A proven approach to process optimization is the lean management tool Value Stream Mapping (VSM). By extending the traditional VSM with ecological and social indicators, a methodological instrument is created for a holistic evaluation of production processes along the three pillars of sustainability. At the same time, digital technologies in the context of Industry 4.0 offer new possibilities to automatically evaluate production data and design data-driven decision support.

The objective of this work is the development of an algorithm for the automated identification and evaluation of sustainability potentials in industrial value streams. In this context, existing approaches and tools for considering sustainability aspects in production systems are analyzed. The developed algorithm combines established decision support methods with production-related indicators and uses digital structures for the systematic evaluation of sustainability potentials. The application is primarily aimed at manufacturing companies that want to extend classical lean methods with sustainability aspects and identify fields of action based on data. The practicability and effectiveness of the developed algorithm are finally validated and discussed using a real industrial case study.

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1 Introduction

1.1 General introduction to the subject area and Problem definition

The climate crisis is one of the most significant global challenges of the 21st century. Environmental degradation and climate change are disrupting natural systems, impacting ecosystems, economies, and the well-being of billions of people (United Nations Environment Programme, 2024). At its core, the crisis is driven by human-induced greenhouse gas (GHG) emissions (Ipcc, 2022). The global mean surface temperature has increased by approximately 1°C since the late 19th century, largely due to the sharp rise in GHG emissions. Industry is a significant contributor to these emissions, accounting for 20.3% of GHG emissions within the EU in 2023 (European Parliament, 2024).

To prevent irreversible social and economic consequences, drastic reductions in GHG emissions are essential. Global and regional initiatives such as the European Green Deal, specifically the Green Deal Industrial Plan (GDIP) with the Net Zero Industry Act (NZIA) and the Fit for 55 package, require manufacturing companies to adopt sustainable practices (Veugelers et al., 2024) and (Europäische Union, 2021).

In this context, the manufacturing sector, one of the largest emitters (Stratmann et al., 2023), faces challenges closely linked to the operational implementation of sustainability. A lack of knowledge, missing strategies, and limited practical guidance often led to sustainability aspects being insufficiently considered in production system design and decision-making. Furthermore, there is no consistent integration of sustainability KPIs into production planning and control, making it difficult to monitor performance across the entire value chain. As a result, companies often lack real-time insights into resource use, waste streams, and emissions, which prevents the timely identification of inefficiencies and targeted improvement actions. Addressing these challenges requires effective and structured operational methods that enable companies to identify and act on sustainability potentials within their production processes.

One such method is Value Stream Mapping (VSM), which provides a visual and analytical framework to uncover inefficiencies and opportunities for improvement (Sihn et al., 2016). In this context, the use of KPIs allows organizations to quantitatively assess performance and evaluate the effects of implemented improvements (Berndt et al., 2024). Currently, VSM is primarily applied at the operational level, sometimes incorporating sustainability KPIs to identify potentials and bottlenecks along the value stream by measuring actual values and defining target values. However, its reliance on numerous manual operations, such as drawing up the current state map, calculating sustainability KPIs, identifying lean and green waste, and developing the future state map limits scalability and consistency. Moreover, the lack of automated integration of sustainability KPIs into VSM workflows leads to fragmented and incomplete data, which is updated only irregularly rather than in real time.

The absence of tools, such as algorithms, present a significant challenge for organizations striving to integrate sustainability aspects into their operations effectively. To address this gap, this thesis develops an algorithm for assessing sustainability performance in a structured, value stream-oriented manner. The algorithm is designed to automatically identify sustainability potentials within production processes, thereby advancing sustainability goals in the manufacturing sector, fostering more sustainable production practices.

In this context, the key issues can be classified into the following problem areas:

Problem 1: Knowledge gaps and challenges regarding sustainability lead to the insufficient consideration of sustainability aspects in current production systems

Problem 2: The lack of the integration of sustainability KPIs into current production systems hinders the efficient monitoring of the sustainability performance across the entire value chain

Problem 3: The absence of robust sustainability assessment systems impedes the continuous monitoring and evaluation of economic, environmental, and social impacts, thereby hindering the identification of inefficiencies within organizational processes

1.2 Research questions and Aim of the Thesis

Based on the previously mentioned problem, the following research questions arise:

Research Question 1: How are sustainability aspects considered in current production systems?

Research Question 2: What approaches and tools enable the identification of sustainability bottlenecks and potentials in manufacturing companies?

Research Question 3: How can an algorithm be designed to identify economic, environmental, and social sustainability potentials in production systems?

In the initial phase, the theoretical foundations will be established to provide a comprehensive understanding of the core concepts and principles. In addition to the Principles of Value Stream Mapping, the Triple Bottom Line by John Elkington, as well as relevant standards and regulations, will be discussed, which are fundamental for supporting organizations in the implementation of sustainable practices and ensuring compliance with legal requirements. Furthermore, the significance of sustainability

KPIs will be examined, with particular emphasis on their role in measuring and assessing sustainability progress across the economic, environmental and social dimensions. In this context, the fundamentals of algorithms will also be introduced, with a focus on their role within sustainability assessment, highlighting their potential to enable data-driven decision-making and automation in the evaluation of sustainability performance.

Subsequently, a systematic literature review (SLR) will be conducted to identify and analyze the prevailing approaches and tools employed in production systems that consider sustainability aspects. To ensure a comprehensive overview of existing methodologies, the reviewed scientific publications will be systematically categorized according to their key contribution and area of application.

Building on the approaches and tools identified in SLR, the primary objective of this thesis is to develop an algorithm that enables the identification, evaluation, and prioritization of sustainability-related potentials within production processes. This algorithm is intended to support decision-makers in manufacturing by providing transparent, data-driven insights into economic, environmental, and social impacts across the value stream, thus fostering more effective and holistic sustainability management at the operational level.

By extending the traditional Value Stream Mapping (VSM) approach to systematically incorporate sustainability dimensions, the algorithm aims to close the gap between conceptual sustainability frameworks and their operational implementation. It will enable organizations to automatically identify critical improvement areas and highlight the KPIs that most significantly influence the sustainability performance of each production process. Validated with empirical manufacturing data, this algorithm is designed to enhance the reliability, robustness, accuracy, and practical applicability of sustainability assessments within production systems, contributing to more sustainable and competitive industrial practices.

The aim of this thesis can be broken down into the following objectives:

Research Objective 1: Identifying and analyzing existing approaches and tools used in production systems to address sustainability

Research Objective 2: Identifying approaches and models for detecting sustainability bottlenecks and potentials in manufacturing companies

Research Objective 3: Developing an algorithm that enables the automated identification and evaluation of sustainability-related potentials within production systems

1.3 Organization and Structure of the thesis

The foundation of this work is based on the design-science paradigm, as proposed by (Hevner et al., 2004). The thesis is structured, as suggested by the research questions, into a theoretical and a practical part. In **Chapter 1**, the current situation is explained, followed by the derivation of the resulting problem statement, the presentation of the research questions and objectives of the thesis, and the determination of the Structure of the thesis. **Chapter 2** outlines the research methodology, encompassing the Design Science method. In **Chapter 3**, the relevant theoretical foundations are presented, and the key terms are defined, which are essential for the subsequent development of the algorithm. An in-depth systematic literature review on existing approaches, tools, and relevant sustainability KPIs for real-time monitoring in production systems is provided in **Chapter 4**. **Chapter 5** focuses on the development and detailed explanation of the Sustainability Potentials Detection Algorithm (SPDA), which is empirically tested and evaluated in **Chapter 6** using manufacturing data to assess its effectiveness, accuracy, reliability, and reproducibility. **Chapter 7** contains the conclusion and limitations, followed by the outlook and Future Work in **Chapter 8. Chapter 9** includes the list of relevant publications, sustainability KPIs identified through SLR and the source code of SPDA. **Chapters 10** includes the bibliography. **Chapter 11 to 14** provide the lists of illustrations, equations, tables and abbreviations.

2 Methodology and Methodical Approach

The foundation of this work is based on the design-science paradigm, which has its origins in engineering and the sciences of the artificial, and primarily focuses on problem solving through the creation of innovative artifacts such as ideas, practices, technical capabilities, or products (Hevner et al., 2004).

The research process in the design-science paradigm begins with the conception of innovative artifacts, which are then implemented. The artifacts in a research project can take various forms, such as a construct, model, method, or an instantiation (Hevner et al., 2004). The artifact in this work will be an algorithm, that fulfil the requirements based on the previously mentioned problem.

The framework used in this work is based on Hevner's Three-Cycle View, which connects the contextual environment, design science activities, and scientific knowledge to ensure high-quality research. The three cycles are the Relevance Cycle, the Design Cycle and the Rigor Cycle, as shown in Figure 1.

The Rigor Cycle is essential to connect the design-science paradigm and the underlying knowledge base (Hevner et al., 2004). The theoretical foundations and the results from SLR serve as the knowledge base for this work. A variety of scientific databases are available for relevant literature. For SLR, the „Scopus“ database was chosen. A search strategy was developed based on the research problem and objectives to identify and explore relevant literature.

The Relevance Cycle bridges the gap between the project's environment and the Design Science Research by establishing key criteria for the developed artifact (Hevner et al., 2004). Building on insights from the systematic literature review and established methodologies, specific requirements for the algorithm are meticulously identified. These requirements ensure that the algorithm addresses practical needs within production systems.

The Design Cycle involves a continuous process of constructing the artifact, assessing its performance, and refining it based on the feedback obtained. This cycle is fundamentally reliant on the Relevance and Rigor Cycles, as it draws upon their inputs to establish a solid basis for the development of the necessary artifact (Hevner et al., 2004). In this work, the Design Cycle focuses on developing and testing the algorithm using manufacturing data. The algorithm undergoes several iterations of refinement, incorporating feedback from operational supervisors and insights gained during empirical testing. The designed algorithm will contribute to the knowledge base (Rigor Cycle).

The final step is to communicate the results in the form of a master's thesis, which also discusses open questions and provides an outlook for future research and applications.

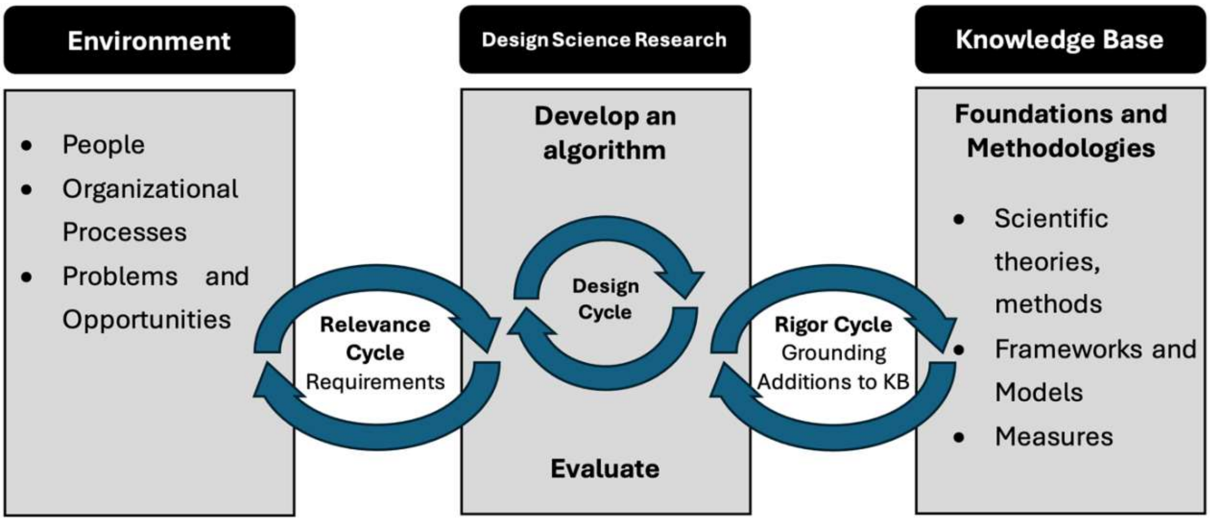

Figure 1: Design Science Research Cycles adapted from (Hevner et al., 2004)

3 Theoretical Principles

In this chapter, the key theoretical principles are introduced that are essential for understanding concepts and sustainable practices. First, the chapter "Principles of Value Stream Mapping" explains the concept of value stream mapping, which plays a central role in improving manufacturing processes. Next, the chapter "Sustainability in the Context of Production Systems" highlights the economic, environmental and social dimensions of sustainability using the Triple Bottom Line framework. It also addresses relevant standards and regulations that guide the implementation of sustainable processes and practices. Furthermore, it focuses on measuring sustainability through key performance indicators that enable objective assessments of performance. Finally, the chapter "Fundamentals of Algorithms" presents the basic concepts of algorithms, which play a crucial role in the analysis and optimization of production systems. Together, these sections lay the theoretical foundation for advancing and optimizing production processes in line with sustainability goals.

3.1 Principles of Value Stream Mapping

Value Stream Mapping (VSM) is a methodological tool used to analyze the current state of the value stream, reaching from suppliers to customers, while also facilitating the creation of a future state map. Originating from the Toyota Production System (TPS), VSM has become one of the most widely recognized methodologies in Lean Management (Niemann et al., 2021). By employing simple and standardized symbols, VSM provides a systematic and visual representation of the entire value stream, encompassing its key elements and interdependencies (Erlach, 2019). By mapping out these processes, VSM enables the identification of inefficiencies, potentials and bottlenecks in production systems (Niemann et al., 2021).

The term VSM is made up of the words "value" and "stream". In a production process, the input goods are given added value through value creation. From a business perspective, the increase in value is driven by production efforts that are closely linked to the product feature. Therefore, from a business perspective, the value of a product can be defined using the Equation 1 (Erlach, 2019):

$$\boldsymbol{Value = Manufacturing\ costs + Profit\ margin\ determined\ by\ the\ company}$$

Equation 1: Value of a product

Stream refers to the sequence of production activities in which physical materials or information move from one workstation to the next (Erlach, 2019).

Thus, the term "value stream" refers to a series of interconnected processes, both value-adding and non-value-adding, that are necessary to produce a product. These processes encompass the entire flow, from the procurement of raw materials to the delivery of the finished product to the customer (Sihn et al., 2016). Building on this understanding of the value stream, the next section will explore the key phases involved in VSM.

3.1.1 Phases in Value Stream Mapping

The phases in VSM provide a structured approach to analyzing and improving the flow of materials, information, and processes, as illustrated in Figure 2. The following sections will provide a detailed explanation of each phase in VSM, highlighting the key activities and objectives involved in successfully implementing this method.

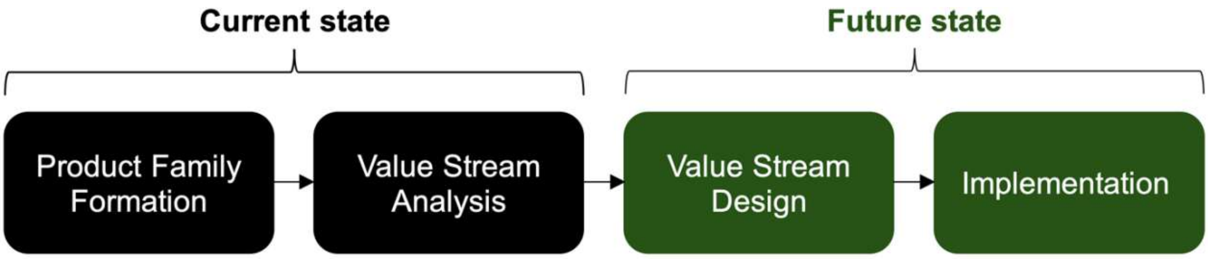

Figure 2: Phases in Value Stream Mapping, adapted from (Sihn et al., 2016)

Product Family Formation

The initial step is to choose the product and the related production processes that will be targeted for improvement. Different products often have different manufacturing processes, and to ensure clarity in the Value Stream Analysis (VSA), it is essential to group products with similar production characteristics into product families (Niemann et al., 2021). A product family is defined as a set of products that are manufactured using similar production steps and, typically, share the same or similar machinery and equipment. A product family involves products that require comparable operations, which may include assembly, machining, or finishing (Sihn et al., 2016). Tools such as the product family matrix will be used for the formation of product families (Erlach, 2019).

In the Product Family Matrix, the vertical axis lists the different products being manufactured, while the horizontal axis captures the key production stages necessary to produce those products, as shown in Figure 3. The matrix essentially serves as a mapping tool, linking products with their corresponding operations, machinery, and tools. The cells of the matrix indicate whether a particular production step is used for a given product, allowing manufacturers to identify which products share similar production requirements (Koch, 2015). In addition to aligning products with common production steps, the product family matrix can incorporate a variety of other criteria to further refine the grouping of products into families. These factors contribute to a more accurate representation of production realities and demand characteristics, thereby supporting more effective decision-making (Sihn et al., 2016).

	Production stages				
Products	***Turning***	***Milling***	***Assembly***	***Testing***	**Product Family**
A	X		X	X	1
B	X		X	X	
C		X	X	X	2
D		X	X	X	

Figure 3: Product Family Matrix, adapted from (Erlach, 2019)

As an intermediate step between the formation of product families and VSA (current state), the customer demand analysis is conducted. This step aims to avoid both underproduction and overproduction by aligning the production with actual customer demand. Therefore, the takt time should be calculated using Equation 2, which represents the time needed to produce a product to meet customer demand (Niemann et al., 2021).

$$\textit{Takt time} = \frac{\textit{Available Production Time per period}}{\textit{Customer demand per period}}$$

Equation 2: Takt time

The prerequisite for Equation 2 is stable and predictable customer demand per period. Any fluctuations in customer demand can disrupt the system's efficiency, potentially requiring adjustments in production capacity, scheduling, or resource management in order to ensure a consistent flow and meet customer expectations, while avoiding excessive lead times and unnecessary costs (Niemann et al., 2021).

Value Stream Analysis

The next step is the Value Stream Analysis (VSA) of the current state, which involves identifying and visualizing the required processes, including the flow of materials and information, for a specific product family (Sihn et al., 2016). For the mapping of the current state, standardized symbols are employed, as shown in Figure 4. Processes like turning, assembly etc., as well as logistical activities such as shipping etc., are all represented in the map. Transport is differentiated in internal (e.g., by forklift) or external (e.g., by truck) and is illustrated using arrows (Sihn et al., 2016).

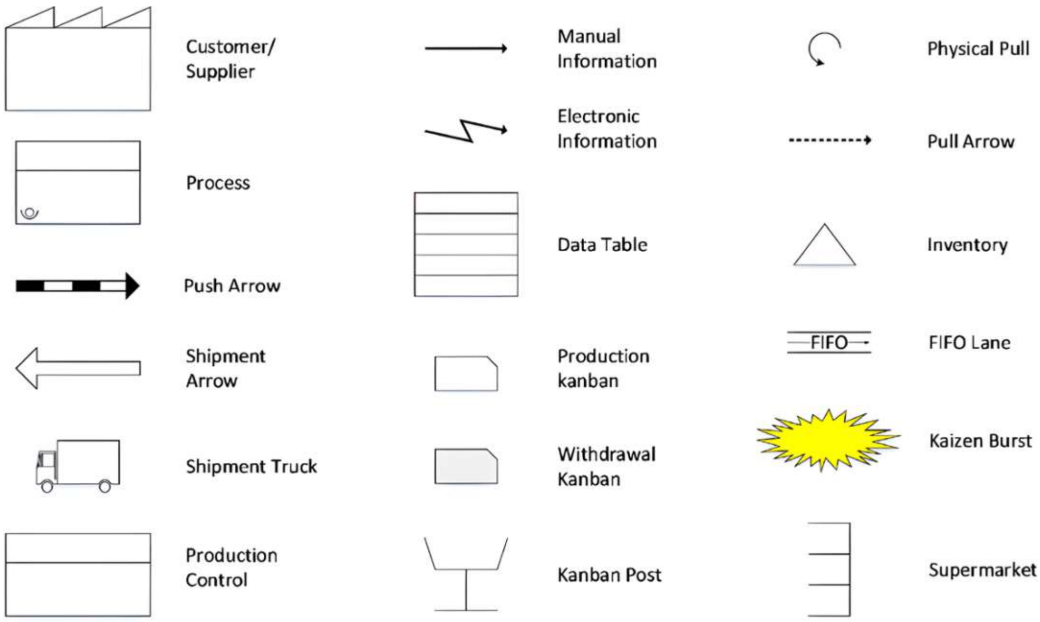

Figure 4: Standardized symbols for VSM (Batra et al., 2016)

In VSA, all activities involved in the production of a product are traced back in order to identify weaknesses, waste, and inefficiencies (Schuh et al., 2014). An example of the visualization of the current state as a value stream map is shown in Figure 5.

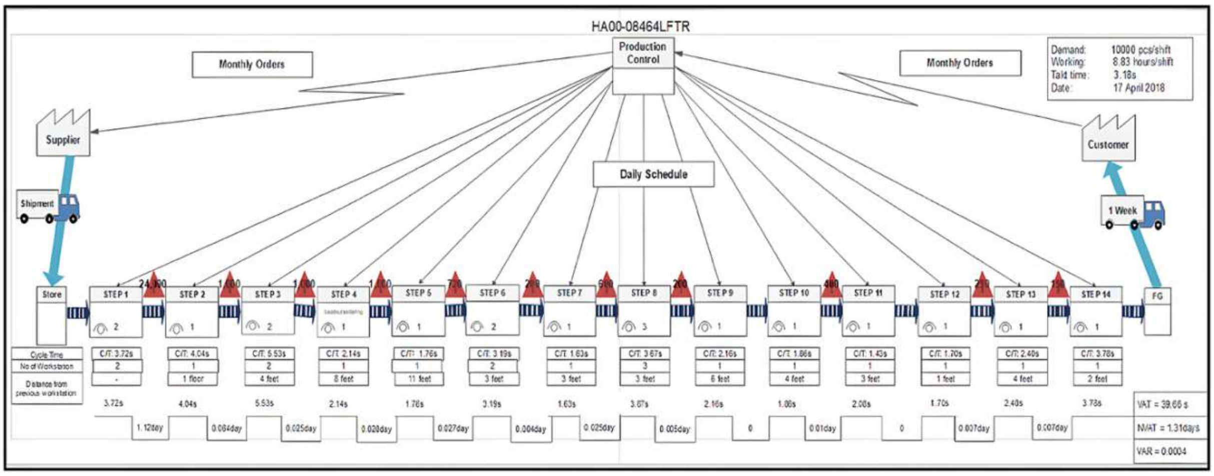

Figure 5: Value stream map (Osman Zahid et al., 2020)

The current state of the value stream can be visualized through on-site manufacturing data, such as total lead time, processing times and inventory. These data points help to determine the throughput time, which is a critical measure of efficiency in a manufacturing system. It can be simplified and calculated using the Equation 3:

$$\textit{Throughput time} = \frac{\textit{Number of parts in inventory}}{\textit{Customer demand per day}}$$

Equation 3: Throughput time

Equation 3 provides a rough estimate of how long it takes on average, for a part to be processed and delivered to the customer, based on current inventory levels and demand rates. Inventory levels of raw materials or goods between production stages are depicted using a triangle symbol. A timeline is positioned below the value stream map, which consists of the upper level and lower level. The upper level represents the processing times for each step in the value stream. The lower level illustrates the amount of time that raw materials or goods remain in inventory or in a waiting state before being processed to the next step. A Value stream map also includes the production planning system (e.g., ERP or MES system), which is displayed centrally above the value stream (Sihn et al., 2016).

VSA serves as a key input for Value Stream Design (VSD), enabling targeted improvements to enhance efficiency and streamline processes.

Value Stream Design

Value Stream Design (VSD) focuses on creating a desired future state for the value stream, with the goal of aligning the flow of value with takt time to ensure that production processes are synchronized with customer demand (Sihn et al., 2016). Efficiency is increased by eliminating waste and reducing non-value-adding activities throughout the value stream (Niemann et al., 2021). In TPS, waste is systematically categorized into seven types (Erlach, 2019). The seven types of waste are overproduction, high inventory levels, transportation, unnecessary movements, waiting, inefficiencies within the production process itself, and defects (Niemann et al., 2021). To systematically eliminate waste in the production process, seven guidelines are defined, as illustrated in Figure 6 (Sihn et al., 2016). By following these principles, manufacturing companies can improve the overall process efficiency.

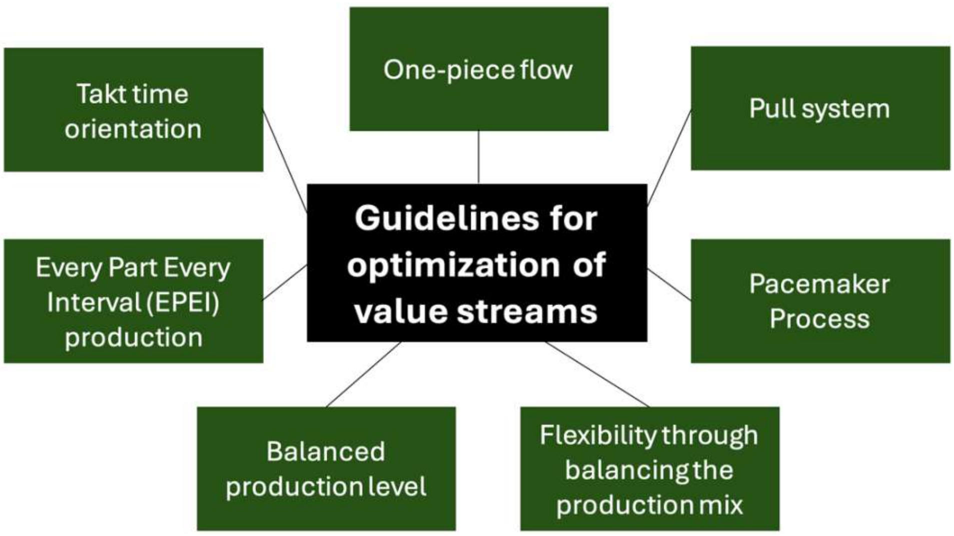

Figure 6: Guidelines for optimization of value streams, adopted from (Sihn et al., 2016)

The first key guideline is to align production processes with takt time in order to meet customer demand. This allows for responsive and demand-driven scheduling (Sihn et al., 2016). Operator Balance Chart (OBC) is an effective tool to visualize the cycle times of each production stage. It serves as a visual aid for balancing production flow, reducing inefficiencies, and ensuring that processes are synchronized with customer demand. Operator Balance Chart is a bar graph that displays the cycle times and the takt time (horizontal line), as illustrated in Figure 7. Cycle times that are longer than the takt time indicate bottlenecks in the production processes, as these processes are taking longer than required to meet customer demand. Conversely, cycle times that are shorter than the takt time visualize waste, as production is happening faster than needed, potentially leading to overproduction or underutilization of resources (Niemann et al., 2021).

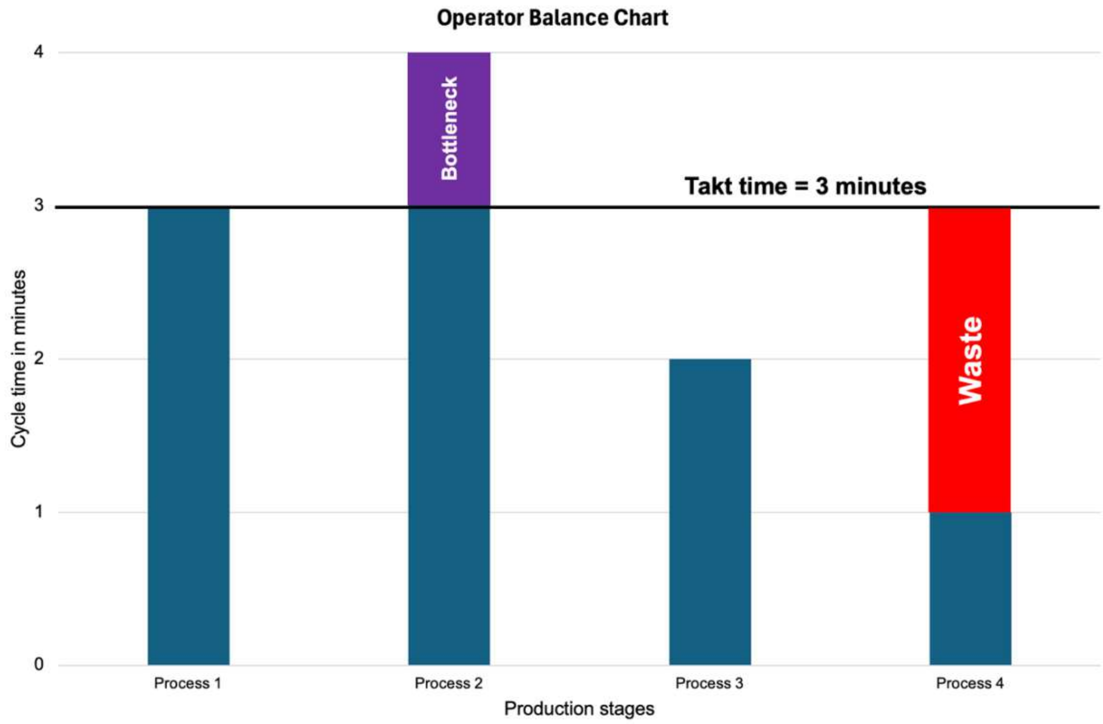

Figure 7: Operator Balance Chart, adopted from (Sihn et al., 2016)

The second guideline is the implementation of one-piece flow. One-piece-flow is characterized by a production of a single unit, where the part is directly passed to the next process without being halted or stored between steps (Erlach, 2019). The goal is to adhere to the takt time and to produce only what is required at each step. This approach eliminates intermediate inventories between processes, reducing the need for buffer spaces and handling effort. To enable one-piece flow manufacturing, workstations must be arranged according to the sequence of operations (Sihn et al., 2016).

The third guideline is the implementation of a pull system. In a pull system, Kanban cards are used to control the material supply and production. Each card is linked to a specific container, with the quantity matching the amount specified on the card. This ensures a consistent and controlled material flow, helping to balance supply and demand, reduce inventory, and align production with customer needs (Erlach, 2019).

In pull systems, it is essential to identify the point where the control of the value stream occurs (fourth guideline). This point is referred to as the "Pacemaker Process" and determines the production rhythm for the entire value stream. The choice of the point also affects lead time and scheduling. It is crucial that material flows downstream from the Pacemaker Process to subsequent processes without interruption. Thus, the production scheduling point should be placed as far upstream as possible (Sihn et al., 2016).

The fifth guiding principle is flexibility through balancing the production mix. To meet varying customer demands with minimal lead time, production of different products should be evenly distributed over a set period. This approach helps prevent bottlenecks and ensures that production is flexible enough to respond to changes in customer demand. Additionally, it results in small inventory buffers, allowing for a more responsive and efficient manufacturing process (Sihn et al., 2016).

To ensure a smooth and stable production flow, and to respond immediately to issues with corrective actions, a balanced production level is targeted (sixth guideline). To improve production control, smaller production orders are released at regular intervals. These small work units are defined by the “pitch” interval, which is calculated using Equation 4 (Sihn et al., 2016).

$$\boldsymbol{1\ Pitch = Takt\ time * Container\ quantity}$$

Equation 4: 1 Pitch

The seventh guideline is Every Part Every Interval (EPEI) production. In EPEI production, the goal is to manufacture each product in a defined time interval, ideally with the smallest possible batch sizes. This approach ensures that all product variants are produced regularly to maintain flexibility and responsiveness to customer demand (Erlach, 2019).

Implementation

To implement the future state, both Flow Kaizen and Process Kaizen are applied. Flow Kaizen primarily focuses on improving the flow of materials and information, aiming to optimize how these elements are moved throughout the value stream. In contrast, Process Kaizen targets the flow of people and processes, with particular emphasis on the interactions between employees and their respective manufacturing processes. Since achieving the future state at once is rarely feasible, value stream loops introduce improvements step-by-step. Clear objectives and assigned responsibilities ensure accountability and effective progress monitoring (Sihn et al., 2016).

In summary, VSM provides a structured framework for visualizing, analyzing, and optimizing production processes with a focus on operational efficiency and waste reduction. However, as the manufacturing industry face increasing pressure from regulatory requirements and stakeholder expectations, the scope of process optimization must expand beyond traditional efficiency metrics. Integrating sustainability considerations, which encompass economic, environmental and social dimensions, into VSA becomes essential for achieving long-term resilience and compliance with evolving frameworks and regulatory standards. The subsequent chapter therefore introduces the foundational concepts of sustainability.

3.2 Sustainability in the Context of Production Systems

Sustainability, often referred to as the Triple Bottom Line (TBL), is an essential concept that underscores the need for businesses and organizations to consider not only their economic performance but also their environmental and social impacts. The following chapter provides a definition of sustainability and elaborates the concept of TBL by John Elkington.

Definition and Importance of Sustainability

The United Nations (UN) provides one of the most widely recognized definitions of sustainable development, which is defined as follows (Brundtland, 1987):

"Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs."

This definition incorporates two fundamental concepts, which are the priority of essential human needs and the limitations of technology and social organization in meeting the present and future needs (Brundtland, 1987). In essence, sustainability refers to a state in which a balance is achieved between economic growth, environmental protection and social inclusion, as illustrated in Figure 8 (UNITED NATIONS, n.d.).

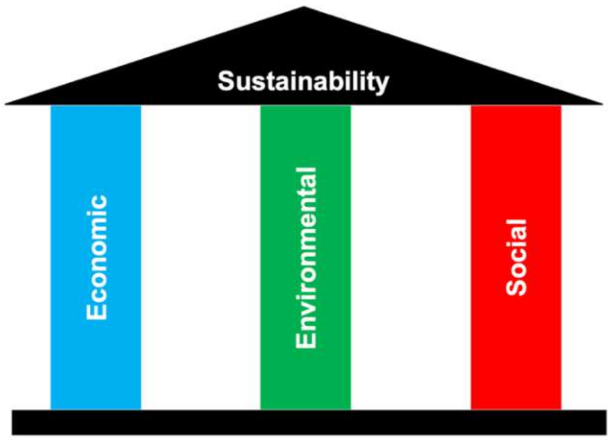

Figure 8: Three dimensions of sustainability, adopted from (Purvis, 2019)

Building upon this fundamental understanding of sustainability, TBL concept provides a practical and widely adopted model for evaluating organizational performance across the economic, environmental, and social dimensions, which are discussed in detail in the following sections.

3.2.1 The Triple Bottom Line in Manufacturing

The Tripple Bottom Line (TBL), introduced by John Elkington, is a reporting framework designed to encourage companies to assess and communicate their impact on the economy, environment and society. TBL focuses on the accounting and measurement of economic, environmental, and social factors, enabling a more comprehensive and sustainable view of corporate performance (Elkington, 1997). In the manufacturing sector, the TBL framework helps assess not only financial outcomes but also the environmental footprint of production processes and the social implications of labor practices (Dewi et al., 2023). By expanding traditional financial metrics to include environmental and social indicators, the TBL creates new categories of value, often referred to as the "Three P´s" (People, Planet, and Prosperity), as shown in Figure 9 (UW ONLINE COLLABORATIVES, 2022). This approach is also commonly known in the literature as the "Three Pillars Model" (Handelszeitung, n.d.).

Figure 9: Three P´s of TBL (Stedman & Gillis, 2024)

Economic Bottom Line – Prosperity

This dimension refers to the economic success of a company. In accounting, the "Bottom Line" denotes the final line in the profit and loss statement (P&L). It represents more than just profit and loss, because it also includes sustainable business models (Elkington, 1997). For manufacturing companies, economic sustainability involves optimizing production efficiency through new manufacturing technologies and reducing waste, ensuring that operational improvements contribute to long-term value creation and resource-efficient operations (Abubakr et al., 2020). To ensure long-term economic sustainability for a company, it is essential to create stable value over time. This includes achieving long-term financial stability, fostering innovation, and maintaining strong demand for its products or services (Elkington, 1997).

The shear zone between prosperity/profit and planet, illustrated in Figure 9, addresses the issue “Eco-efficiency” (Stedman & Gillis, 2024). “Eco-efficiency” refers to providing goods and services at competitive prices that meet human needs and enhance quality of life while progressively reducing ecological impacts and resource intensity across the entire lifecycle. In manufacturing, eco-efficiency can be achieved through lean management tools such as 5S and SMED, as well as energy-saving initiatives and circular economy strategies (García-Alcaraz et al., 2021) and (Jovane et al., 2008). The goal is to achieve eco-efficiency and secure economic success without negative impacts on society or the environment (Elkington, 1997).

Environmental Bottom Line – Planet

This dimension focuses on the environmental impacts of a company (Stedman & Gillis, 2024). It includes a closer examination of "critical natural capital" and “renewable, replaceable, or substitutable natural capital”. Critical natural capital ensures the preservation of life and the integrity of ecosystems, while the second form of natural capital, as the name suggests, can be renewed, repaired, or substituted. In manufacturing, this involves optimizing material and energy usage in order to enhance environmental performance (Li et al., 2017). Long-term sustainable businesses can improve their environmental performance by measuring environmental impacts through KPIs such as life cycle impacts of products, energy consumption, material and water usage at production sites (Elkington, 1997). The goal is to protect the planet and minimize the negative effects on the environment (Arowoshegbe & Emmanuel, 2016).

The shear zone between planet and people highlights the connection between environmental protection and social responsibility, as shown in Figure 9. Companies that enhance the quality of life by adopting environmentally friendly and sustainable practices can achieve both ecological and social benefits (Graver, 2024). In manufacturing, this may include adopting measures to optimize material usage and reduce waste, while at the same time implementing workplace practices and technologies that improve operator safety, ergonomics, and reduce exposure to harmful substances such as dust and noise (Atoillah & Hartini, 2021).

Social Bottom Line - People

The social dimension of TBL refers to the extensive impact a company has on society and individuals, particularly concerning the well-being of its employees, communities, and future generations. According to (Elkington, 1997), social capital is defined as human capital, which includes elements such as public health, education, skills, and overall social welfare. The goal is to promote beneficial and fair business practices towards the workforce, human capital, and the wider community (Elkington, 1997). In manufacturing, this includes ensuring safe working conditions, providing training for employees, and designing work environments that minimize physical strain while promoting ergonomic efficiency (Utama & Abirfatin, 2023). Additionally, companies can further influence people positively and support future generations by ensuring fair hiring practices, providing equitable wages, and offering health insurance to employees (Miller, 2020), (Arowoshegbe & Emmanuel, 2016).

The shear zone between prosperity/profit and people addresses the issue “Socio-economic sustainability” and highlights the connection between economic success and social responsibility. Socio-economic sustainability entails the integration of business practices that promote social equity and economic stability, thereby creating value for all stakeholders. This approach includes entrepreneurial activities aimed at combating poverty, creating job opportunities, and fostering fair and just environments (Elkington, 1997).

To effectively implement the principles of TBL, organizations require clear guidelines and a structured approach to ensure that sustainability efforts are consistent and verifiable across industries. This makes international standards and regulatory frameworks essential for guiding companies toward measurable and comparable sustainability outcomes.

3.2.2 Regulatory Drivers for Industrial Sustainability

To address climate change and promote sustainable development, regional and global efforts such as the Paris Agreement and the European Green Deal are important initiatives. To complement these efforts, both organizations and governments are adopting frameworks and standards that help structure and measure progress toward climate and sustainability goals.

To better understand the necessity and impact of regulatory frameworks, it is essential to examine the historical development of global GHG emissions. This provides context for the urgency and scope of current climate policy efforts.

Evolution of GHG Emissions

Figure 10a shows the global annual CO_2 emissions released into the atmosphere from the combustion of coal, natural gas, liquid fuels, cement manufacture, and gas flaring (CO_2^{FF}) over the past two centuries. Approximately 50% of the CO_2 emissions produced by human activities remain in the atmosphere. The remaining CO_2 emissions are absorbed by the oceans and the terrestrial biosphere, predominantly trees. As shown in Figure 10a, the global population has significantly increased since 1950, which has also contributed to the massive rise in CO_2 emissions (Salawitch et al., 2017).

The diagram in Figure 10b illustrates the historical evolution of GHG emissions from 1825 to 2020, highlighting major industrial developments that have shaped emission trends. Starting with the early industrial revolution, emissions rose gradually due to coal-powered steel manufacturing. The second industrial revolution brought electrification and mass production, accelerating emissions. A significant post-World War 2 industrial boom, driven by oil and chemical industries, caused a steep increase. Despite the oil shocks of the 1970s, globalization and the rapid industrialization of emerging economies, particularly China fueled further growth (Salawitch et al., 2017).

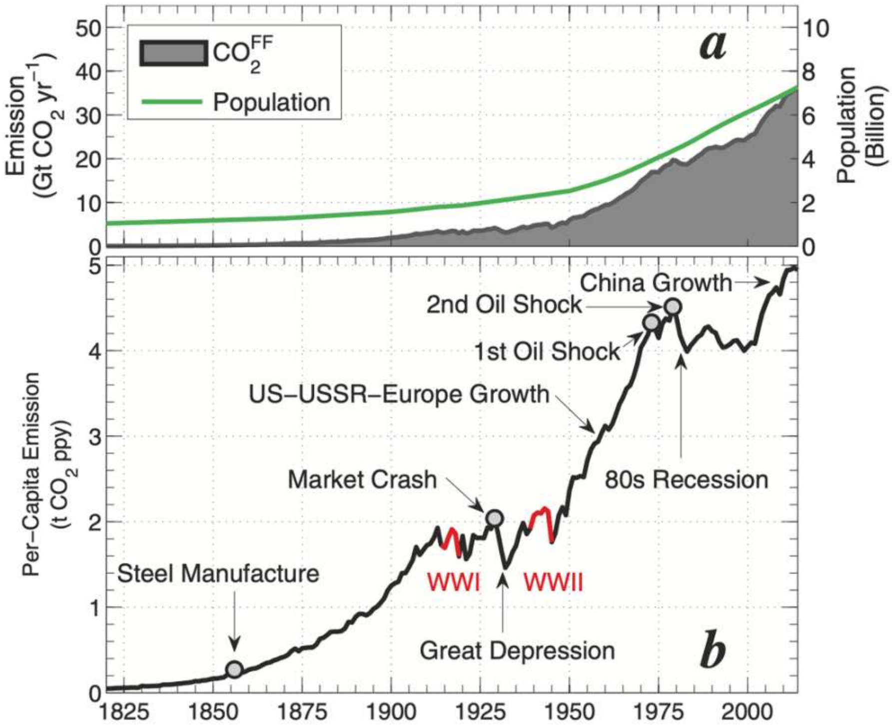

Figure 10: Total global emission of CO_2 (Salawitch et al., 2017)

To prevent the catastrophic consequences of rising in CO_2 emissions, largely driven by the rapid industrial expansion and energy-intensive production methods of the past two centuries, sustainability frameworks set out ambitious objectives to limit global warming and promote global efforts toward more sustainable industrial development.

3.2.3 Sustainability Frameworks and Reporting Standards

In response to these urgent needs, a growing number of international agreements, regulatory frameworks, and reporting standards have been introduced to guide the transition toward a climate-neutral economy. Among the most significant initiatives are the Paris Agreement, the European Green Deal, the EU Taxonomy regulation and the Global Reporting Initiative.

Paris Agreement

The Paris Agreement, adopted on 12. December 2015 at the 21st Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCCC) in Paris, represents a significant milestone in the global effort to combat climate change (United Nations Climate Change, n.d.). The agreement followed the Kyoto Protocol and emphasized the importance of universal participation and long-term sustainability (Salawitch et al., 2017) and (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie, 2024).

The central goal of the Paris Agreement is to limit global average temperature rise to well below 2°C above pre-industrial levels, with a further effort to limit the temperature increase to 1.5°C (United Nations Climate Change, n.d.). Achieving this requires transformations in industrial production, including materials efficiency, enhanced recycling, decarbonization of production processes and the adoption of very low- or zero-emission technologies (Shukla et al., 2022).

To meet the Paris Agreement's ambitious climate targets, nations must not only transform their industrial processes but also establish clear guidelines for action. One such framework is the set of Nationally Determined Contributions (NDCs) for GHG emission reductions and climate actions, which may include both quantitative and qualitative goals, along with defined timelines (United Nations, n.d.-b) and (United Nations & Development Programme, 2023). In the industrial sector, these contributions drive efforts toward energy-efficient manufacturing, the adoption of cleaner technologies, and the implementation of circular economy principles (Shukla et al., 2022).

Another important aspect of the Paris Agreement is its reliance on global stocktaking, which occurs every five years to communicate, update, and enhance their NDCs (United Nations, 2015) and (United Nations, n.d.-a). The results guide updates to climate action plans, promoting technological innovations and stronger mitigation efforts (United Nations Climate Change, n.d.).

To translate these global goals into concrete regional policies, EU introduced the European Green Deal, aiming to lead the path toward climate neutrality among its member states.

European Green Deal

Building on the global framework established by the Paris Agreement, the European Green Deal (EGD), adopted on December 2019, specifies a broad array of measures designed to facilitate the transition to a low-carbon, sustainable economy within Europe (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie, n.d.) and (Europäische Kommission, 2021). This strategic document outlines EUs commitment to assume a global leadership role in the fight against climate change. It outlines the goal of reducing emissions by at least 55% by 2030 ("Fit for 55" legislative package), compared to 1990 levels (Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie, n.d.). In February 2024, the European Commission introduced an additional interim target of a 90% reduction in emissions by 2040 (European Commission, n.d.-d).

EGD includes measures for industry to drive a sustainable economic transformation. Three central components of this comprehensive strategy are the Green Deal Industrial Plan (GDIP), the Critical Raw Materials Act (CRMA), and the Net-Zero Industry Act (NZIA), as illustrated in Figure 11 (European Commission, n.d.-d).

GDIP, introduced by the European Commission in February 2023, aims to align European industry with sustainability objectives while enhancing its global competitiveness. Its primary goal is to increase the EU's manufacturing capacity for CO_2-neutral technologies and products, which are crucial for meeting the ambitious climate targets (European Commission, 2023).

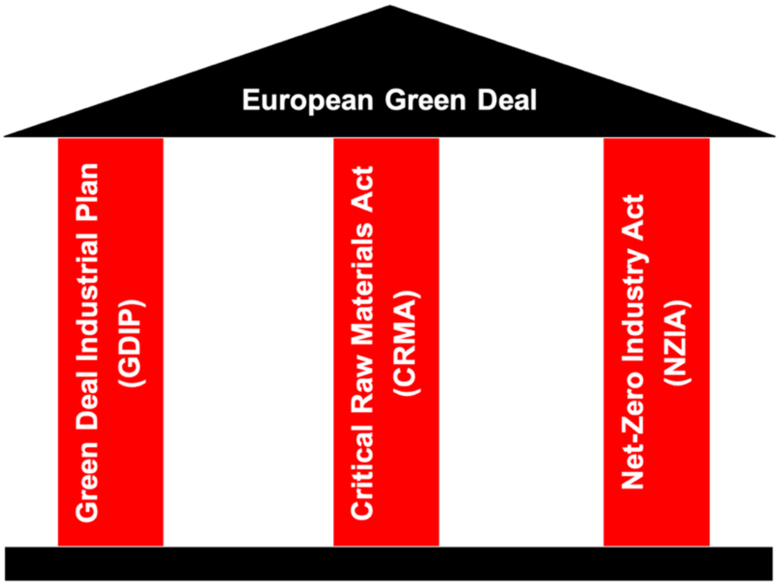

Figure 11: Key Initiatives of European Green Deal

CRMA is another key initiative of GDIP, aimed at ensuring the supply of critical raw materials essential for the green transition and the digital economy. NZIA is a regulatory framework designed to transform the EU's industrial base into a fully climate-neutral production sector by 2050 through adoption of clean technologies (European Commission, n.d.-c).

Building on these strategic initiatives, regulatory frameworks such as the EU Taxonomy regulation further operationalize EDG's sustainability ambitions by providing a standardized classification system for environmentally sustainable economic activities. As industries increasingly align with such frameworks, effective reporting standards become essential for tracking progress and ensuring accountability. Instruments like the EU Taxonomy Regulation and the Global Reporting Initiative establish benchmarks for companies to disclose their environmental impact, guiding them toward greater transparency and consistency in their sustainability efforts (European Commission, n.d.-a) and (Global Sustainability Standards Board (GSSB), 2021b, p. 1).

EU Taxonomy regulation

EU Taxonomy regulation, introduced in 2020, plays a pivotal role in guiding companies and investors through the transition to a greener economy and net zero, particularly by establishing clear criteria for sustainable investments and promoting activities such as the shift to a circular economy and the reduction of pollution (European Commission, n.d.-a).

EU Taxonomy regulation explicitly includes manufacturing activities within its scope, setting technical screening criteria to determine whether industrial production processes substantially contribute to environmental objectives, such as climate change mitigation or transition to a circular economy, as shown in Figure 12. This framework provides a standardized reference for the manufacturing industry to align investment and operations with the EU’s sustainability targets (European Commission, 2020).

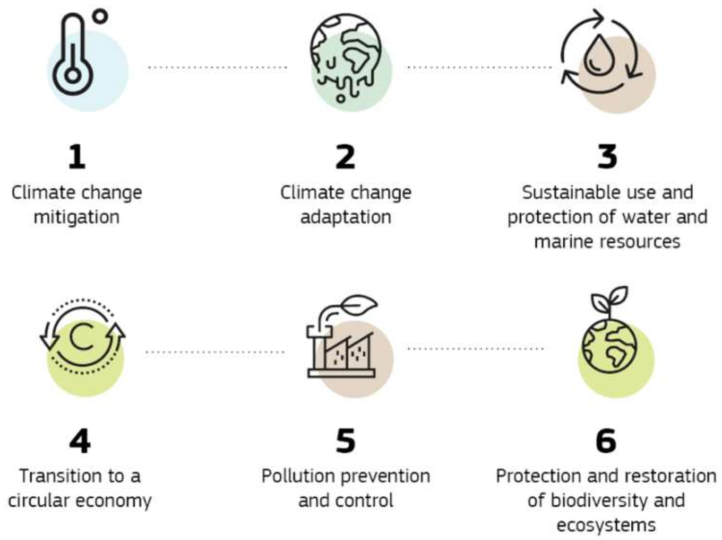

Figure 12: Six objectives of the EU-Taxonomy (European Commission, n.d.-b)

Building on this, standardized reporting frameworks such as GRI Standards facilitate transparent disclosure of sustainability performance by organizations.

Global Reporting Initiative

Global Reporting Initiative (GRI) Standards provide a structured and comprehensive set of standards for sustainability reporting, ensuring clear and detailed disclosures of economic, environmental, and social impacts (Global Sustainability Standards Board (GSSB), 2021b, p. 1). GRI standards are divided into “Universal Standards (GRI 1, GRI 2, and GRI 3)", "Sector Standards", and "Topic Standards", as shown in Figure 13.

GRI 1 outlines the fundamental principles of sustainability reporting, including accuracy, balance, clarity, comparability, completeness, sustainability context, timeliness and verifiability (Global Sustainability Standards Board (GSSB), 2021b, p. 1).

GRI 2 outlines specific requirements for sustainability reporting within organizations, expecting organizations to describe value creation across the entire value chain and assess economic, environmental, and social impacts from their operations and products (Global Sustainability Standards Board (GSSB), 2021c, p. 2).

GRI 3 outlines the methodological steps required to identify material topics with the most significant impacts on the economy, environment, and society.

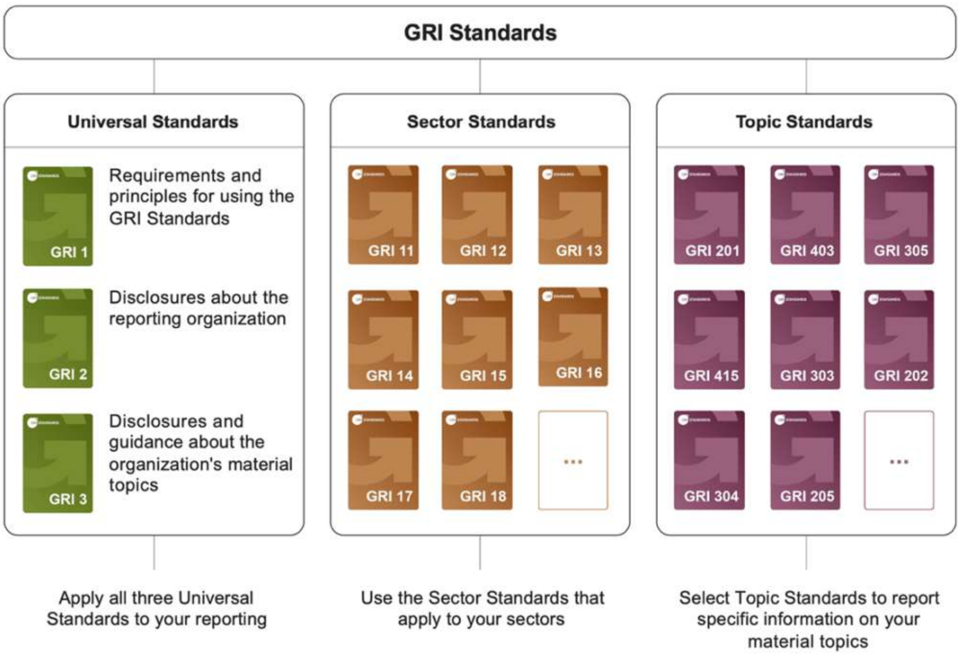

Figure 13: GRI standards (Global Sustainability Standards Board (GSSB), 2021a)

The process of determining material topics encompasses the understanding of the organizational context, identification of actual and potential impacts, assessment of the significance of these impacts and prioritization of the most relevant topics for the sustainability report (Global Sustainability Standards Board (GSSB), 2021d, p. 3).

The set of GRI Standards also includes 40 Sector Standards (GRI 11, 12, 13, …), organized into four distinct groups (Global Sustainability Standards Board (GSSB), n.d.-a), which are "Basic Materials and Needs," "Industrial," "Transport, Infrastructure, and Tourism," and "Other Services and Light Manufacturing" (Global Sustainability Standards Board (GSSB), 2021e). Sector-specific standards improve reporting quality by addressing industry challenges and enhancing transparency (Global Sustainability

Standards Board (GSSB), n.d.-a). In addition, Topic Standards (Series 200, 300, 400) guide organizations in reporting on their material topics (Global Sustainability Standards Board (GSSB), n.d.-b).

Building on the discussion of sustainability frameworks, including the Paris Agreement, the European Green Deal, the EU Taxonomy regulation, and the GRI Standards, the following section introduces sustainability KPIs. These indicators are essential for systematically measuring and monitoring performance across the economic, environmental, and social dimensions of TBL, providing organizations with actionable insights to identify improvement areas, and align operations with sustainability goals.

3.2.4 Sustainability Key Performance Indicators

To make sustainability measurable and actionable within manufacturing companies, it is essential to define and monitor KPIs. Sustainability KPIs provide a structured way to evaluate performance across the economic, environmental, and social dimensions of TBL, while aligning measurement with recognized frameworks such as the GRI Standards and the EU Taxonomy regulation.

According to (Parmenter, 2020), KPIs are metrics that highlight the most crucial aspects of organizational performance, vital for both the current and future success of the organization. They are regularly updated to allow real-time tracking and swift responses to any changes. KPIs are strategically aligned with the organization's goals and are simple, clear, and easy to understand. KPIs are intricately integrated within the organizational framework, allowing them to be directly attributable to specific teams. This deep embedding ensures that accountability can be assigned (Parmenter, 2020).

Traditional accounting standards provide well-established frameworks for the measurement of profit, thus rendering the economic bottom line relatively clear and measurable for many businesses and organizations (Kenton, 2024). In contrast, the assessment of the People and Planet dimensions requires the adoption of new, more comprehensive indicators. Notable among these are the Human Development Index (HDI) and the Index of Sustainable Economic Welfare (ISEW), which aim to provide a more nuanced understanding of societal and environmental well-being (Elkington, 1997).

By linking KPIs to established standards like GRI and EU Taxonomy, organizations not only ensure consistent and credible sustainability reporting but also generate structured, quantifiable data that can feed advanced analytical tools. This data provides the foundation for algorithmic approaches, enabling systematic evaluation of value stream processes and identification of sustainability potentials.

3.3 Fundamentals of Algorithms

This chapter presents a comprehensive analysis of algorithms, beginning with a clear definition to establish a foundational understanding of the term. In particular, the focus is placed on algorithms that support sustainability performance assessments in industrial value streams, highlighting their role in enhancing economic, environmental, and social outcomes. Additionally, the chapter examines the key properties of algorithms, which are essential for their successful implementation in various computational tasks and are particularly relevant for sustainability-related decision-making, as they ensure that the analysis is transparent, reproducible, and reliable. Furthermore, this chapter introduces the theoretical foundations underlying the Sustainability Potentials Detection Algorithm (SPDA) for identifying sustainability potentials within value streams and demonstrates how structured algorithmic approaches can systematically reveal areas for improvement across multiple sustainability dimensions. In order to establish a solid conceptual foundation for the subsequent analysis, it is essential to define the term “algorithm” and examine its fundamental characteristics.

Definition and Purpose

An algorithm is a well-defined, step-by-step procedure designed to solve a specific problem. It takes a set of input values, processes them through a sequence of clearly defined and unambiguous steps, and generates a set of output values (O’Regan, 2018). The specific steps and operations performed by the algorithm are determined by the nature of the problem and the context in which the algorithm is applied (Yang, 2021). In sustainability assessments within manufacturing contexts, algorithms are applied to process and evaluate large amounts of heterogeneous data, enabling decision-makers to identify improvement potentials in environmental, economic, and social dimensions (Soltani et al., 2019). Algorithms can be implemented through computer programs, typically written in a programming language, which enables their execution (O’Regan, 2018). According to (O’Regan, 2023), the speed of the program depends on several factors, including the algorithm used, the input values, the way the algorithm is implemented in the chosen programming language, the compiler, the operating system, and the hardware of the computer. A significant characteristic of many algorithms is their iterative nature, where a process is repeated multiple times until the desired outcome is achieved (Yang, 2014).

Building on this understanding of what algorithms are and how they function, it is important to examine their key properties, which define their effectiveness and applicability in various contexts.

Properties

An algorithm is distinguished by several fundamental properties. Firstly, it exhibits clarity, where each step is precisely and unambiguously defined. Secondly, the property of finiteness ensures that an algorithm terminates after a finite number of steps, providing a definite outcome. Furthermore, an algorithm must possess executability, meaning that all instructions are feasible and can be effectively implemented in practice. Algorithms also have clearly defined inputs, which lead to specific outputs upon execution, making their behavior predictable. Finally, determinism is a crucial property, as it ensures that, for identical inputs, an algorithm will consistently produce the same output, thereby guaranteeing predictable and reproducible results (LMU München, Institut für Informatik, 2014).

These core properties enable algorithms to effectively address complex challenges. In sustainability assessments, they are particularly useful for optimizing industrial processes and identifying improvement opportunities across TBL dimensions.

3.3.1 Algorithmic Approaches in Sustainability Assessment

Optimization algorithms play a pivotal role in sustainability assessments and decision support systems. Particularly in the context of industrial value chains, algorithmic approaches enable the systematic identification of sustainability potentials. These methods are especially effective in integrating heterogeneous information sources, structuring complex decision-making processes, and generating transparent and reproducible outcomes (Soltani et al., 2019).

Building on the identification of sustainability potentials, a structured evaluation of KPIs is essential. The Analytic Hierarchy Process (AHP) provides an effective method for systematically weighting these KPIs.

Weighted Evaluation of Sustainability KPIs using AHP

For comprehensive sustainability evaluations, it is crucial to analyze and prioritize KPIs associated with each dimension of sustainability, thereby enabling a structured assessment of their contribution to the fulfillment of strategic business objectives and long-term sustainability targets. AHP is used to systematically weight sustainability KPIs by facilitating pairwise comparisons, which quantify the relative importance of each criterion in relation to others (Dewi et al., 2023).

Focus group discussions are conducted to perform pairwise comparisons of sustainability KPIs using Saaty's fundamental scale. The outcomes of these comparisons are organized into a pairwise comparison matrix A, as presented in Equation 5. The weights for each sustainability KPI are then derived through the eigenvalue method, which involves normalizing matrix A (Equation 6) to obtain matrix A1, calculating the eigenvector W (Equation 7), the eigenvalues W_i (Equation 8) and the maximum eigenvalue λ_{max} (Equation 9). The final step in the AHP procedure is the assessment of consistency of the judgments, performed by calculating the Consistency Index (CI) and Consistency Ratio (CR) according to Equation 10 and Equation 11, respectively. A CR value below 0.10 indicates acceptable consistency of the pairwise comparison matrix (Dewi et al., 2023).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{21} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$$

Equation 5: Results of the pairwise comparison transferred into matrix A

$$a_{ij}^{'} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \text{ for } i,j = 1, 2, 3, \ldots n$$

$$A_1 = \begin{bmatrix} a_{11}^{'} & a_{12}^{'} & \cdots & a_{1n}^{'} \\ a_{21}^{'} & a_{21}^{'} & \cdots & a_{2n}^{'} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}^{'} & a_{n2}^{'} & \cdots & a_{nn}^{'} \end{bmatrix}$$

Equation 6: Normalized matrix A1

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix}$$

Equation 7: Eigenvector W

$$W^{'} = AW = \begin{bmatrix} W_1^{'} \\ W_2^{'} \\ \vdots \\ W_n^{'} \end{bmatrix}$$

Equation 8: Eigenvalue W_i

$$\lambda_{max} = \frac{1}{n}\left(\frac{W_1'}{W_1} + \frac{W_2'}{W_2} + \ldots + \frac{W_n'}{W_n}\right)$$

Equation 9: Eigenvalue λ_{max} for the pairwise comparison between indicators

$$CI = \frac{\lambda_{max} - n}{n-1}$$

Equation 10: Consistency Index

$$CR = \frac{CI}{Random\ Index\ (RI)}$$

Equation 11: Consistency Ratio

While AHP is primarily used to determine the relative importance of sustainability KPIs through structured expert judgment, these resulting weights can further serve as input for more comprehensive multi-criteria evaluation methods (Soltani et al., 2019).

Integrating AHP Weights into Multi-Criteria Evaluation: TOPSIS

A commonly used Multi-Criteria Decision-Making (MCDM) method is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) algorithm, which ranks alternatives based on their closeness to an ideal sustainability solution (Soltani et al., 2019). The application of the TOPSIS algorithm involves several distinct steps, which are depicted in Figure 14. The sequence of steps ensures that both the relative importance of KPIs and the performance of alternatives across multiple criteria are systematically considered.

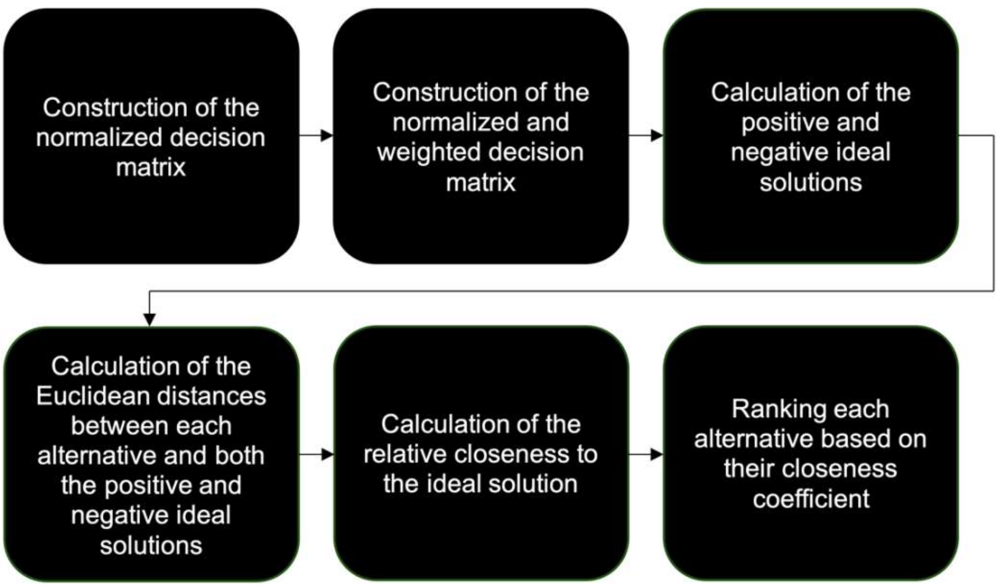

Figure 14: Steps for the TOPSIS algorithm, adopted from (Soltani et al., 2019)

The first step is to construct the normalized decision matrix using Equation 12, where each row represents a work step, and each column corresponds to a sustainability indicator (Soltani et al., 2019).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i}^{m} x_{ij}^{2}}}, j = 1,2,3,\ldots,n;\ i = 1,2,3,\ldots\ldots,m$$

Equation 12: Normalized decision matrix

After normalization, each element in the matrix is multiplied by the corresponding weight of the criterion, as shown in Equation 13, to obtain the weighted values (Soltani et al., 2019).

$$V_{ij} = \ n_{ij} \times w_j \quad j = 1,2,3,\ldots,n;\ i = 1,2,3,\ldots\ldots,m$$

Equation 13: Weighted normalized values

The next step is to calculate the (positive) ideal and (negative) anti ideal solutions based on the maximum and minimum values in the weighted matrix, as shown in Equation 14 and Equation 15 (Soltani et al., 2019).

$$A_i^+ = \{(\max V_{ij} \mid j \in J), (\min V_{ij} \mid j \in J') \mid i = 1,2,3,\ldots m\}\{V_1^+,\ V_2^+,\ V_3^+,\ldots,\ V_n^+\}$$

Equation 14: Ideal solution

$$A_i^- = \{(\min V_{ij} \mid j \in J), (\max V_{ij} \mid j \in J') \mid j = 1,2,3,\ldots n\}\{V_1^-,\ V_2^-,\ V_3^-,\ldots,\ V_n^-\}$$

Equation 15: Anti-ideal solution

The Euclidean distances between each alternative and both the ideal and anti-ideal solutions are then calculated, as shown in Equation 16 and Equation 17 (Soltani et al., 2019).

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (V_{ij} - A_j^+)^2}, \text{ j=1,2,3,…,n; i=1,2,3,…..,m}$$

Equation 16: Euclidean distances of each alternative from ideal solution

$$S_i^- = \sqrt{\sum_{j=1}^{m} (V_{ij} - A_j^-)^2}, \text{ j=1,2,3,…,n; i=1,2,3,…..,m}$$

Equation 17: Euclidean distances of each alternative from anti-ideal solution

The last step is to calculate the relative closeness to the ideal solution, as shown in Equation 18 (Soltani et al., 2019).

$$C_i = \frac{S_i^-}{S_i^- + S_i^+}$$

Equation 18: Relative closeness to the ideal solution (TOPSIS Score)

The alternatives are subsequently ranked based on their closeness coefficient, which quantifies the relative proximity to the ideal solution. The alternative with the highest closeness coefficient is regarded as the most optimal, as it exhibits the greatest similarity to the ideal solution (Soltani et al., 2019). In addition to TOPSIS, other methods such as Fuzzy EDAS (Evaluation Based on Distance from Average Solution) algorithm can be applied for identifying sustainability potentials in value streams.

Fuzzy EDAS for Enhanced Sustainability Evaluation

Fuzzy EDAS algorithm facilitates the evaluation of alternatives by quantifying the distances of each alternative from an ideal solution, encompassing both positive and negative deviations, as well as from an average solution (Aouag & Soltani, 2023). The fuzzy EDAS algorithm involves several steps, which are depicted in Figure 15.

Figure 15: Steps for the Fuzzy EDAS algorithm

The first step is to calculate the average solution according to each criterion, as shown in Equation 19 (Aouag & Soltani, 2023).

$$AV = \left[\check{av}_j\right]_{1\times m}$$

where

$$\check{av}_j = \frac{1}{n} \oplus_{i=1}^{n} x_{ij}$$

and $\check{av}_j$ presents the average solution with respect to each criterion.

Equation 19: Calculation of the average solution according to each criterion

The second step is to calculate the positive and negative distances from the average solution, as shown in Equation 20 (Aouag & Soltani, 2023).

$$PD = \left[\widetilde{pd}_{ij} \right]_{n \times m}$$

$$ND = \left[\widetilde{nd}_{ij} \right]_{n \times m}$$

where

$$\widetilde{pd}_{ij} = \begin{cases} \dfrac{\max\left(0, x_{ij} \ominus \check{av}_j\right)}{\check{av}_j} & \text{if } j \in BC \\ \dfrac{\max\left(0, \check{av}_j \ominus x_{ij}\right)}{\check{av}_j} & \text{if } j \in NC \end{cases}$$

$$\widetilde{nd}_{ij} = \begin{cases} \dfrac{\max\left(0, \check{av}_j \ominus x_{ij}\right)}{\check{av}_j} & \text{if } j \in BC \\ \dfrac{\max\left(0, x_{ij} \ominus \check{av}_j\right)}{\check{av}_j} & \text{if } j \in NC \end{cases}$$

BC and NC are the sets of beneficial and non-beneficial criteria, respectively.

Equation 20: Calculation of the positive and negative Distances from the average solution

The next step is to compute the weighted sum of positive and negative Distances for all criteria, as shown in Equation 21 and Equation 22 (Aouag & Soltani, 2023).

$$sp_i = \oplus_{j=1}^{m} w_i \, pd_{ij}$$

Equation 21: Weighted sum of positive distances

$$sn_i = \oplus_{j=1}^{m} w_i nd_{ij}$$

Equation 22: Weighted sum of negative distances

The subsequent step involves normalizing the values of sp_i and sn_i, as shown in Equation 23. After this normalization, the appraisal score As_i for all criteria is calculated using Equation 24 (Aouag & Soltani, 2023).

$$sp_i^{(n)} = \frac{sp_i}{sp_{\max}}$$

$$sn_i^{(n)} = 1 - \frac{sn_i}{sn_{\max}}$$

Equation 23: Normalization of sp_i and sn_i

$$As_i = \frac{1}{2}\left(sp_i^{(n)} + sn_i^{(n)}\right)$$

Equation 24: Appraisal score As_i for all criteria

After calculating the Appraisal Scores AS_i for all alternatives, the alternatives are ranked based on the AS_i values. The alternative with the highest AS_i score is considered the best, as it is the closest to the ideal solution (Aouag & Soltani, 2023).

By employing algorithmic reasoning based on formal rules and structured evaluation procedures, algorithms contribute to improving both the consistency and comprehensiveness of sustainability analyses in industrial applications. Building on this premise, various methodological approaches have been developed and applied in the literature to support sustainability-oriented decision-making in industrial contexts. To gain a comprehensive overview of existing solutions and their application domains, a systematic literature review was conducted.

4 State of the art / Literature analysis

4.1 Systematic Literature Review

Definition and Purpose

A systematic literature review (SLR) is a structured and comprehensive method used to identify, evaluate, and synthesize existing research on a particular topic. The primary objective is to explore the research field, examine the current state of knowledge, and assess the relevance of various scientific sources (Booth et al., 2016). The process typically involves defining the research question, selecting relevant databases, developing search strategies, applying inclusion and exclusion criteria to select the most pertinent studies, and evaluating the relevance of the papers in relation to the research questions (Läzer, 2010).

4.1.1 Implementation of SLR in this Thesis

In this work, SLR is conducted, which serves as the foundation for the knowledge base. Based on the research questions and the aim of the thesis, relevant literature is retrieved from the scientific databases “Scopus”. Figure 16 illustrates the comprehensive information and procedural steps employing the PRISMA flowchart to ensure transparency in the selection process, following the standards set out in the PRISMA 2020 statement (Page et al., 2021).

Search Strategy and Database Selection

The search terms were meticulously derived based on the research questions and objectives. These terms consist of several keywords interconnected by Boolean operators (Booth et al., 2016). For the initial search, the terms "sustainability" and "production systems" were used in combination with the AND operator. Additionally, the term “manufacturing” was used as a synonym for “production systems” with the OR operator. Since the focus is on identifying sustainability potentials at the operational level, the term “value stream mapping” was employed in combination with the AND operator. The initial search resulted in 149 publications.

Inclusion and Exclusion Criteria

Further inclusion and exclusion criteria were formulated to make the search more precise and reduce the search results (Booth et al., 2016). All documents published between 2015 and 2025 were included in the search in order to obtain up-to-date information. Only publications, which have German or English as their language, were included in the systematic literature review. 33 documents could not be downloaded or there was no access to the PDF-File, so these documents were excluded. The outcome of the second search in “Scopus” was 106 publications.

Relevance Assessment and Evaluation Criteria

The results of the refined search can be distinguished into relevant and non-relevant reports. The documents were analyzed in more detail by reading through the abstracts in order to assess their relevance. Additionally, seven criteria were defined to assess the relevance of the publications. The seven criteria are "methodology (transparency and comprehensibility of the approach), fields of action (presentation of the derivation of fields of action), technological depth (technical findings such as patents, methods, etc.), comprehensiveness (cross-industry content), independence (degree of independence), innovation (proportion of self-development of methods and models) and industry sector (consideration of manufacturing/production systems)". One point (insufficient, very small contribution) or five points (very good, significant contribution) were awarded per criterion. After considering the inclusion and exclusion criteria and evaluation of the relevance of the publications with the seven criteria, the number of publications was reduced to 44.

Scope and Objectives of SLR in this Thesis

This work excludes publications that explore the application of traditional value stream mapping (in supply chain management) and (Green) Lean principles in non-production settings, such as office and service environments, as well as those focused on waste management. Additionally, it excludes literature examining obstacles and facilitators for green VSM implementation and investigates the disparity between industrial practices and academic research on energy-efficient manufacturing design.

Having outlined the methodology and selection criteria of the SLR, it is essential to clarify its specific objectives within the scope of this thesis. The literature review is conducted with the primary aim of analyzing how sustainability aspects are considered in value streams of manufacturing companies. Since the overarching aim of this thesis is to develop a data-driven approach for the automated detection of sustainability potentials within value streams, it is essential to systematically review existing approaches, frameworks and conceptual models. Furthermore, the review concentrates on the sustainability-related KPIs applied and their weighting, analyzing their significance in industrial contexts. Finally, analyzing the application domains of sustainability-oriented solutions ensures that the developed algorithm remains relevant, transferable, and aligned with the practical requirements of industrial environments.

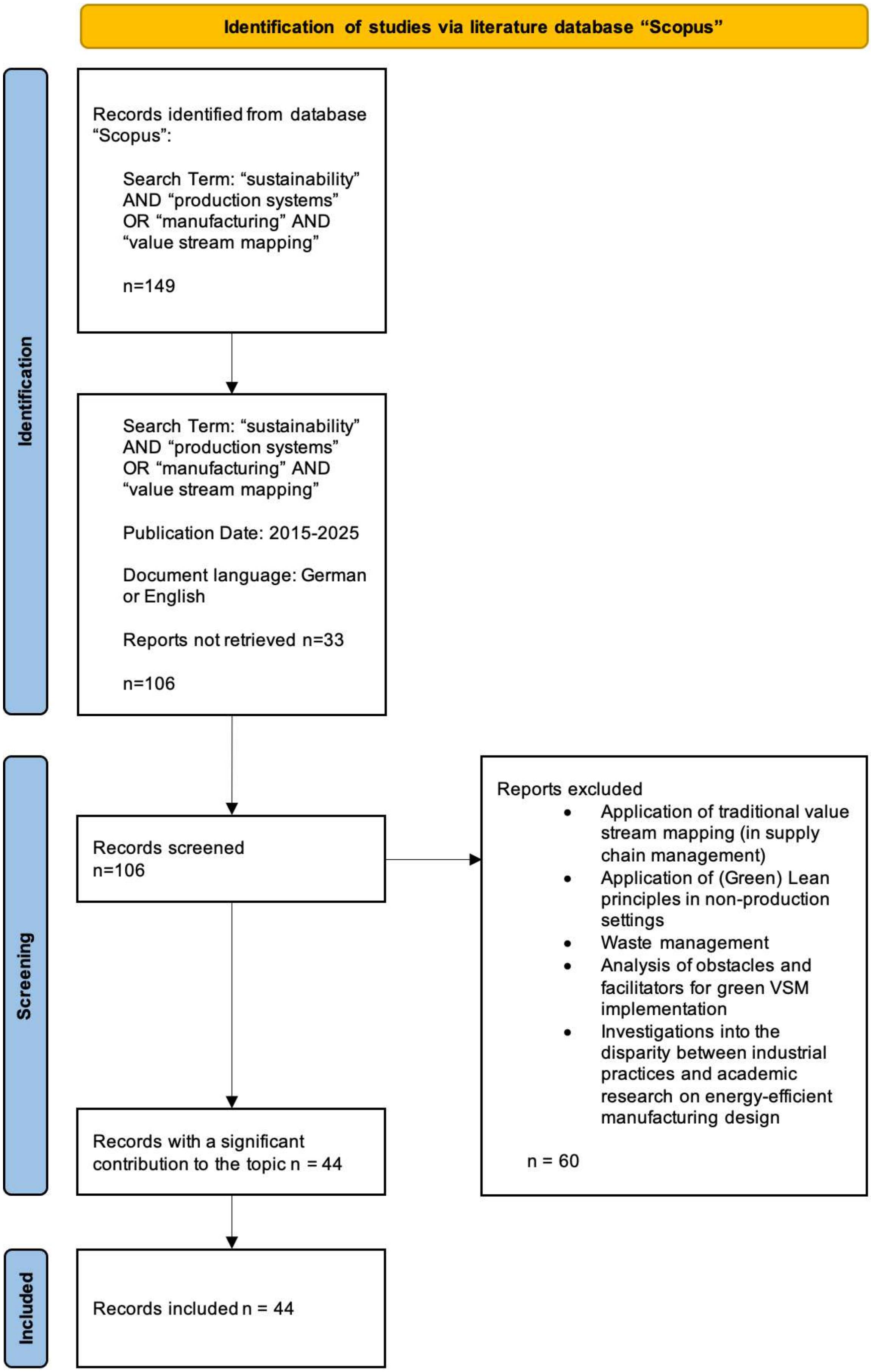

Figure 16: Procedure for the systematic literature review - PRISMA flowchart, adapted from (Page et al., 2021)

4.2 Discussion of Results

This section presents the relevant publications identified through SLR. In this chapter, the focus lies on analyzing the frameworks, conceptual models, application areas, and sustainability dimensions addressed in current research, as well as the approaches used for identifying sustainability bottlenecks and potentials in manufacturing companies. Examining these aspects is essential for the context of this work, as it allows for a comprehensive understanding of how sustainability is operationalized in production systems, and which strategies and tools are applied to assess and enhance sustainability performance. To ensure clarity and facilitate reference, the relevant documents with its key findings and contributions are systematically organized and presented in Table 8.

4.2.1 Evaluation Approaches for Sustainability in Manufacturing

A fundamental step in understanding how sustainability is addressed within production systems is the analysis of approaches, frameworks, and conceptual models employed in existing research. The systematic literature review indicates that the majority of identified approaches build upon Value Stream Mapping (VSM) as a core analytical tool, which is then adapted or extended to integrate sustainability assessment. Identified methodologies are Sustainable VSM (SVSM), Life Cycle - VSM (LC-VSM), Environmental VSM (EVSM), Triple Bottom Line - VSM (TBL-VSM), Green-Integrated VSM (GIVSM), Circular VSM (CVSM), Overall greenness performance - VSM (OGP-VSM) and VSM4S. These variations differ in their scope, sustainability dimensions addressed, and evaluation techniques applied. Figure 17 illustrates the frequency with which each methodology occurs in the reviewed publications.

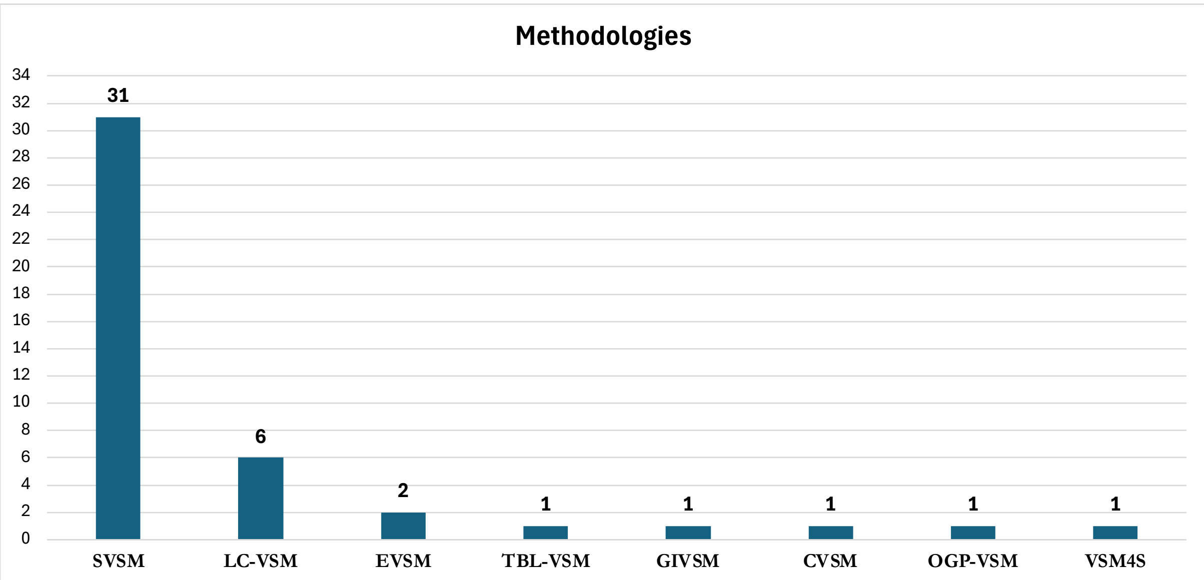

Figure 17: Identified methodologies through SLR

The dataset highlights that SVSM appears 31 times, which is significantly higher than any other methodology. This dominance suggests that SVSM is the most effective, widely accepted and extensively researched approach. The LC-VSM methodology appears six times, indicating moderate acceptance compared to SVSM. This could reflect its relevance in specific applications where a life-cycle perspective is required. While EVSM appears twice, TBL-VSM, GIVSM, CVSM, OGP-VSM, and VSM4S each appear once.

These various methodologies will be discussed in detail to highlight their specific characteristics, applications, and differences.

Sustainable VSM

Sustainable Value Stream Mapping (SVSM) is a methodology that extends the principles of traditional VSM by integrating sustainability dimensions, particularly the TBL indicators (Atoillah & Hartini, 2021). The primary objective of SVSM is to evaluate economic efficiency, ecological and social sustainability performance (Hartini et al., 2020). SVSM is generally implemented in four phases (Figure 18), which, according to (Utama & Abirfatin, 2023), are aligned with the DMAIC (Define, Measure, Analyze, Improve, Control) process. This integration forms the Sustainable Lean Six-Sigma (SLSS) framework for enhancing sustainable manufacturing performance. The DMAIC process is a data-driven quality strategy used to improve processes. This SLSS framework is illustrated in Figure 19.

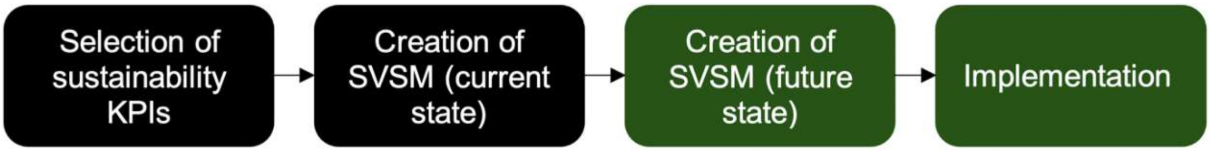

Figure 18: Phases in SVSM, adapted from (Hartini et al., 2020)

In the SLSS framework, the identification and selection of sustainability KPIs take place during the "Define" phase. In this phase, tools such as the SIPOC (Supplier, Input, Process, Output, Customer) diagram and the Delphi method, including the AHP method, are employed. Furthermore, the "Measure and Analyze" phases focus on mapping the current SVSM, which, according to (Hartini et al., 2020), corresponds to the "Creation of SVSM (current state)" phase. The "Improve and Control" phases align with the "Implementation" phase as described by (Hartini et al., 2020). Tools like Failure Mode and Effects Analysis (FMEA) are used to define necessary improvement actions, and subsequent control is conducted using check sheets, which are key characteristics of these two phases (Utama & Abirfatin, 2023) and (Djatna & Prasetyo, 2019).

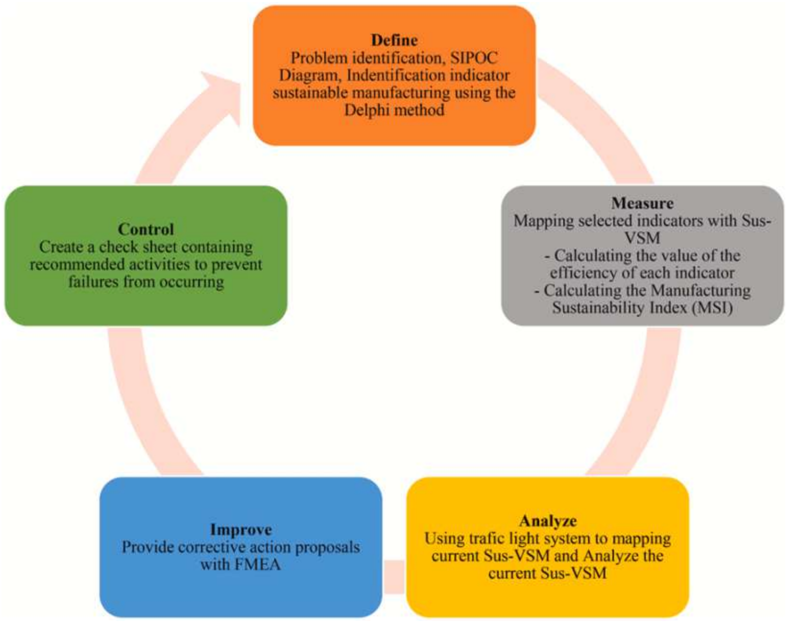

Figure 19: SLSS framework (Utama & Abirfatin, 2023)

In the following, each of the four phases according to (Hartini et al., 2020) is explained in detail.

Selection of Sustainability KPIs

According to (Hartini et al., 2020), the initial phase entails the selection of sustainability KPIs. Choosing suitable indicators for sustainable manufacturing is important, as they offer objective and measurable criteria to evaluate sustainability performance in manufacturing companies (Utama & Abirfatin, 2023). By visualizing these sustainability KPIs and establishing critical efficiency values, processes requiring immediate improvement can be systematically identified (Hartini et al., 2020). The approach for the selection of sustainability KPIs is depicted in Figure 20. Sustainability KPIs are generally selected based on the specific application area, industry or value chain (Soltani et al., 2019). A collection of sustainability KPIs for evaluating sustainability performance in production systems are presented in Table 7.

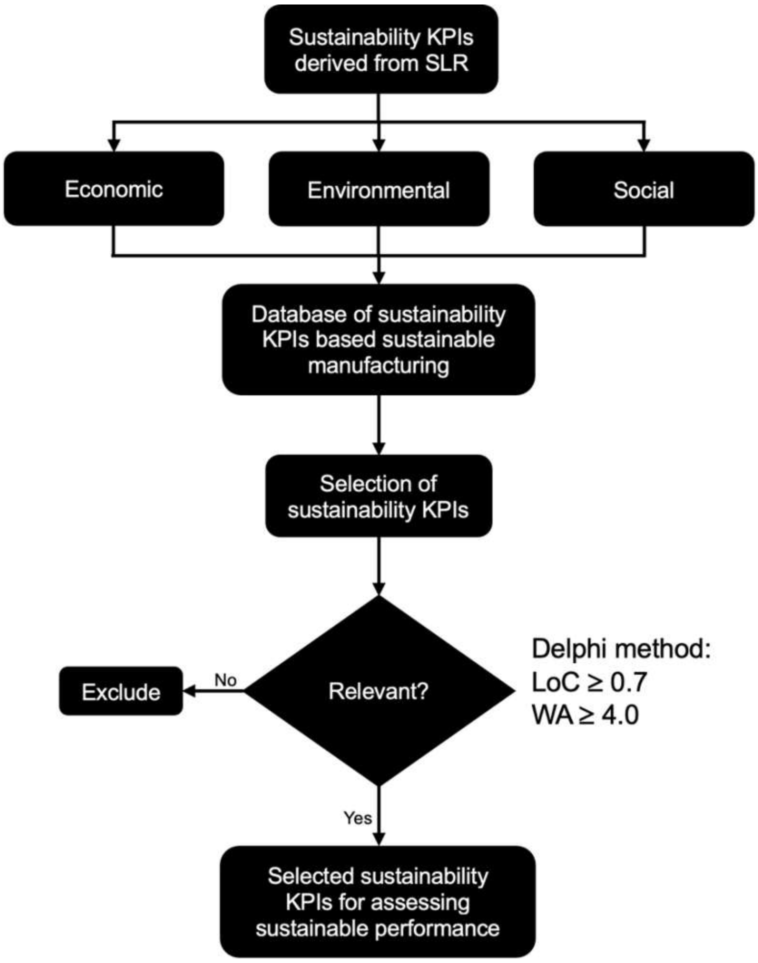

Figure 20: Sustainability KPIs selection process, adopted from (Hartini et al., 2018)

The selection process follows the Delphi method, which is a survey technique used to systematically gather opinions and build consensus on a complex topic. This method involves administering anonymous questionnaires to a group of experts, who provide their responses independently. The process is iterative, allowing for feedback and refinement of opinions until a consensus is reached. According to (Utama & Abirfatin, 2023), this approach guarantees the selection of indicators that are both relevant and reliable. The evaluation of these indicators is conducted through the analysis of the weighted average (WA) and the level of consensus (LoC) (Utama & Abirfatin, 2023). For an indicator to be incorporated into the final set used for sustainability assessment, it must achieve either LoC of at least 0.7 or WA of at least 4.0 (Hartini et al., 2020).

Once the key sustainability KPIs have been established through the Delphi method, AHP method is used to weight these indicators and evaluate the alternatives. This approach allows for a systematic comparison of the various options based on the weighted importance of each sustainability criterion. Focus group discussions are utilized to perform pairwise comparisons between TBL indicators. In this step, experts assess the relative importance of one indicator compared to another, assigning a numerical score on a scale of 1 to 9 (Saaty's scale). The result of the pairwise comparison is transferred into a matrix and the weight for each indicator and alternative is calculated using mathematical methods. The final step of the AHP method is the verification of the consistency of the evaluations. For this, CI and CR are calculated (Dewi et al., 2023).

Creation of the Current State

In these phases, the current state of the value stream is mapped. The SVSM includes the flow of materials and information for a specific product family, and the selected sustainability KPIs along with their efficiency values (Utama & Abirfatin, 2023).

SVSM also includes the "Manufacturing Sustainability Index (MSI)" (Equation 25), which is used in order to determine the overall sustainability performance of the manufacturing process. This comprehensive index encompasses weighted economic, environmental, and social indexes, which are calculated using Equation 26, Equation 27 and Equation 28 (Hartini et al., 2020).

$$\boldsymbol{MSI = \alpha * Ec\_I + \beta * En\_I + \gamma * S\_I}$$

Equation 25: Manufacturing Sustainability Index (MSI)

$$\boldsymbol{Ec\_I = \Sigma w_i * E_i}$$

Equation 26: Economic index

$$\boldsymbol{En\_I = \Sigma w_i * V_i}$$

Equation 27: Environmental index

$$\boldsymbol{S\_I = \Sigma w_i * S_i}$$

Equation 28: Social index

The economic indicator reflects the efficiency related to time, quality, inventory, and cost management within the production system. It evaluates how effectively resources are allocated and utilized to achieve optimal production outcomes while minimizing waste and expenses (Hartini et al., 2020).

The environmental indicator assesses the efficiency of material and energy usage, as well as waste management practices. This dimension highlights the system's capability to reduce environmental impact through sustainable resource utilization and effective waste reduction strategies (Hartini et al., 2020).

The social indicator measures the efficiency of the workforce in terms of health, safety, employee satisfaction, and HR development. It reflects the system's commitment to ensuring a safe and healthy work environment, promoting employee well-being, and fostering continuous professional growth (Hartini et al., 2020).

While the MSI provides a quantitative assessment based on weighted indexes, the "Overall Sustainability Index (SI)" offers an alternative approach for evaluating sustainability performance by comparing actual values (E) against defined target values (S) for each KPI. According to (Saraswati et al., 2024), target and actual values can be obtained through interviews with the head of production or by utilizing the company's historical data. The computation of the Overall SI involves determining the deviation by calculating the difference between the target value (S) and the actual value (E) for each indicator, as shown in Equation 30. These computed values serve as input for the calculation of the SI for economic (SIEc), environmental (SIEn) and social (SISc) factors, as outlined in Equation 29. The weighting of these factors (W) is performed using Saaty's nine-point scale, ensuring a systematic assessment of their relative importance. Finally, the Overall SI is derived by integrating the weighted economic, environmental and social factors, as formulated in Equation 31 (Sari Emelia et al., 2021).

$$SI = \left(\frac{S_{i1}}{E_{i1}}\right)^{Yi1} x \left(\frac{S_{i2}}{E_{i2}}\right)^{Yi2} \ldots x \left(\frac{S_{nij}}{E_{nij}}\right)^{Ynij}$$

Equation 29: SIEc, SISc and SIEn factors

$$Y_{ij} = log\left|S_{ij} - E_{ij}\right|$$

Equation 30: Difference between the target value (S) and the actual value (E)

$$Overall\ SI = (W_{Ec}\ x\ SI_{Ec}) + (W_{Sc}\ x\ SI_{Sc}) + (W_{En}\ x\ SI_{En})$$

Equation 31: Overall SI

Creation of the Future State

The future state of the SVSM is developed using expert knowledge to identify processes requiring immediate improvement. Sustainable bottlenecks and potential improvements are defined, and improvement initiatives are visualized along with their anticipated impact on the MSI or Overall SI (Saraswati et al., 2024). Tools such as Failure Mode and Effects Analysis (FMEA) support the identification of necessary improvements.

Implementation

In the final phase, improvement measures are implemented and monitored. Tools such as Statistical Process Control (SPC) and the use of check charts are employed to effectively monitor the implementation and execution of improvement measures (Utama & Abirfatin, 2023). The phases of SVSM can be iteratively repeated to facilitate ongoing monitoring and rapid response to inefficiencies in the production system (Antomarioni et al., 2018).

While SVSM focuses on improving sustainability within the scope of existing value streams, Life Cycle - VSM takes a broader approach by evaluating sustainability across the entire product lifecycle.

Life Cycle – VSM

Life Cycle (LC) - VSM is an extension of the traditional VSM designed to evaluate the sustainability performance of a company. LC-VSM extends the sustainability assessment to cover the entire lifecycle of a product, integrating economic, environmental, and social KPIs from production to disposal entire (Hartini et al., 2019) and (Kluczek & Bartlomiej, 2020). LC-VSM has four phases, which are depicted in Figure 21.

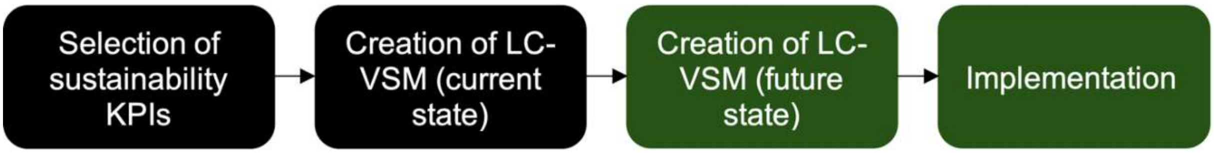

Figure 21: Phases in LC-VSM, adapted from (Horsthofer-Rauch et al., 2021)

According to (Hartini et al., 2019), LC-VSM considers the life cycle of a product, from the pre-manufacturing stage (preparation of raw materials) to manufacturing, consumption (use by the consumer), and the post-consumption stage (disposal, reuse, and recycling), as shown in Figure 22.

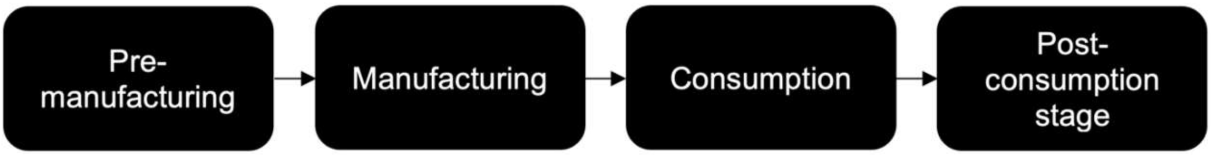

Figure 22: Life cycle of a product, adopted from (Hartini et al., 2019)

The first phase of LC-VSM is the selection of sustainability KPIs. Based on the company's strategy and sustainability objectives, relevant sustainability KPIs are defined for VSA. These KPIs are carefully chosen to provide meaningful insights into the economic, environmental and social aspects of the value stream (Horsthofer-Rauch et al., 2021).

A particular form of LC-VSM is the energy-focused VSM approach based on Life Cycle Assessment (LCA), as presented by (Kluczek & Bartlomiej, 2020). This approach focuses primarily on energy-related aspects of the lifecycle, which leads to the exclusion of time as a relevant KPI in the analysis. To assess sustainability comprehensively, (Kluczek & Bartlomiej, 2020) integrated energy LCA, Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA) into their approach.

The calculation of the environmental impact of each activity is performed using an LCA calculator based on life cycle inventory (LCI) (Samant & Prakash, 2020). According to (Salvador et al., 2021), an LCA calculator can employ the “TRACI” as Life Cycle Impact Assessment (LCIA), which can involve several impact categories. The environmental impacts of a product are quantified in kg CO_2e across its entire life cycle, helping to identify the life phases with the highest and lowest environmental impacts (Samant & Prakash, 2020).

After the selection of the necessary sustainability KPIs, the required data is prepared to represent the current state in LC-VSM. According to (Salvador et al., 2021), the environmental impacts of a production step are calculated using the “Ecoinvent 3.3” database.

According to (Horsthofer-Rauch et al., 2024), process mining can be utilized to visualize the value stream. The implementation of a process mining-based, sustainability-integrated VSM approach demands considerable initial effort. By utilizing a data model tailored to the company’s specific requirements, real-time updates and dynamic changes to the database are facilitated, enhancing the system's flexibility and efficiency in sustainability monitoring and optimization (Horsthofer-Rauch et al., 2024).

Through LC-VSM, the material and energy flows, as well as decision flows, become evident. Using this information, the improvement team can consistently pinpoint internal and external inefficiencies, environmental impacts, and underlying issues that hinder the company’s sustainability performance (Hartini et al., 2019).

After defining the action measures, the LC-VSM of the future state is created, which involves the potential gains from the proposed changes. Before implementing the improvement actions, the future state is discussed in terms of total impacts, specific impacts by process, and Lean Management KPIs (Salvador et al., 2021).

In addition to LC-VSM, another methodology that equally incorporates economic, environmental, and social factors is the TBL-VSM.

Tripple Bottom Line – VSM

The Tripple Bottom Line (TBL) - VSM, presented by (Chavez et al., 2023), integrates sustainability KPIs to evaluate and enhance TBL performance of production systems. The TBL-VSM framework is composed of four key phases, as depicted in Figure 23. In order to select the relevant sustainability KPIs, this approach incorporates traditional Lean Management KPIs, GRI reporting standards, as well as the Science Based Targets initiative (SBTi) and the GHG protocol (Chavez et al., 2023). In the case study presented by (Chavez et al., 2023), TBL-VSM was employed to assess and visualize waste in the production process. The production process of a pharmaceutical company was analyzed, and improvement opportunities were identified across the economic, environmental, and social dimensions.

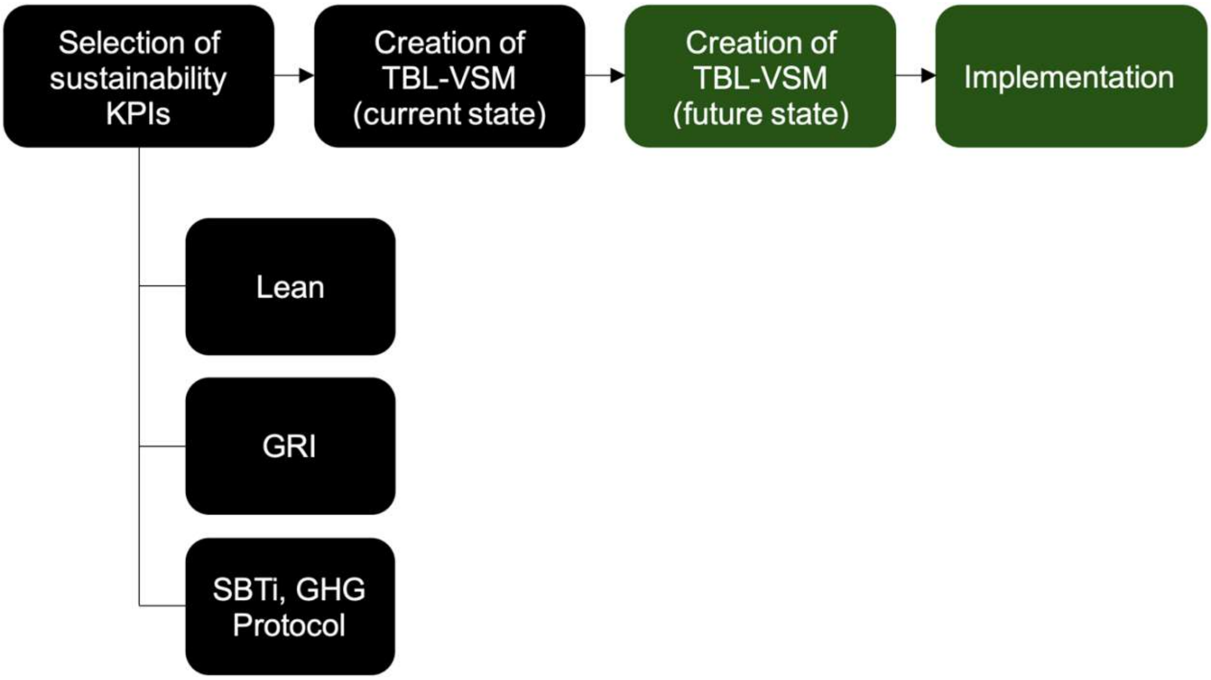

Figure 23: Phases in TBL-VSM, adapted from (Chavez et al., 2023)

At the bottom of the TBL-VSM map, in addition to the Lean Management KPIs, the GRI KPIs are indicated, which are associated with the GRI Topic standards. GRI indicators are utilized to measure and assess improvements across the three pillars of sustainability. According to (Chavez et al., 2023), for measuring the sustainability performance of a manufacturing process, standards 301 to 306 and 403 are recommended.

While TBL-VSM integrates sustainability KPIs across economic, environmental, and social dimensions, VSM4S builds on this by using goal programming to assess these dimensions more systematically.

VSM4S

VSM4S is a methodology that integrates economic, environmental and social dimensions, assessing sustainability performance through a multi-criteria approach grounded in the philosophy of goal programming (Serafim Silva et al., 2024). The VSM4S framework is based on the 5SEnSU model, as illustrated in Figure 24.

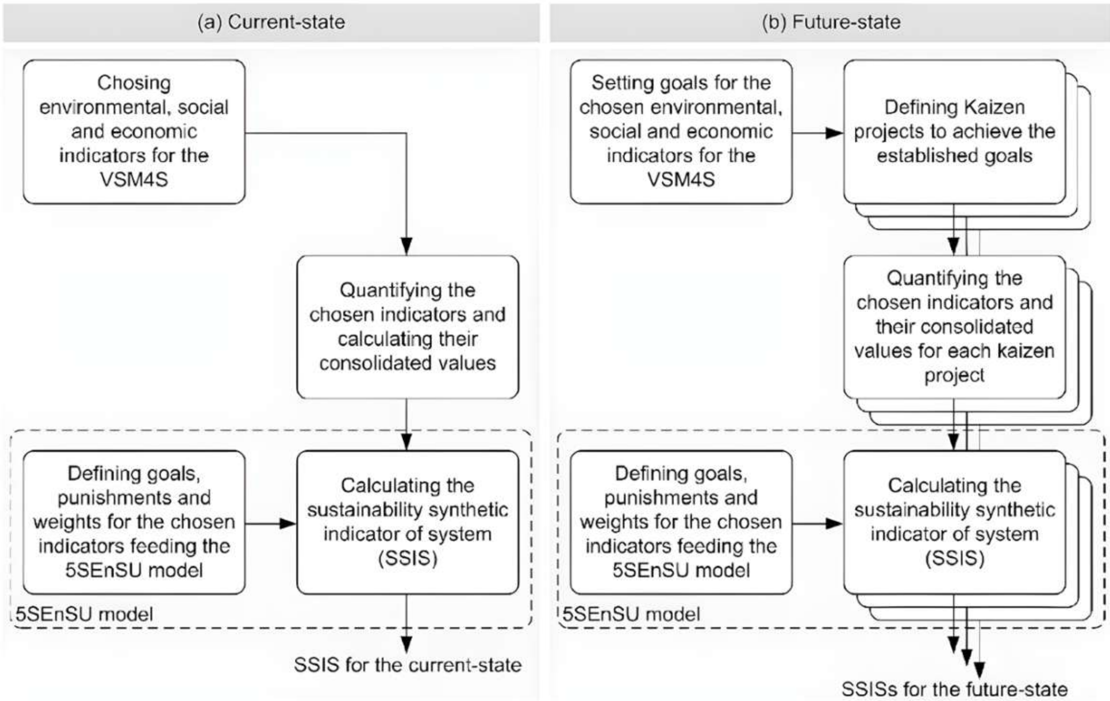

Figure 24: VSM4S framework (Serafim Silva et al., 2024)

Initially, the selection and calculation of economic, environmental, and social KPIs are performed. Within the 5SEnSU model, it is essential to select at least one KPI for each sustainability dimension to enable the application of goal programming philosophy effectively (Serafim Silva et al., 2024).

Next, the goals, penalties, and weights for the selected indicators are defined, which are essential for the 5SEnSU model (goal programming philosophy). To compute the Synthetic Sustainability Indicator of the System (SSIS) for current and future state, specific targets must be established for each sustainability KPI, as the deviation from the target for each indicator contributes to the SSIS calculation. Within the context of goal programming, indicators that fall below the target and are to be maximized, or indicators that exceed the target and are to be minimized, are penalized. An example illustrating the objective of minimizing an indicator is shown in Figure 25, where indicators for systems #2 and #4 exceed the goal and should therefore incur a higher penalty than those for systems #1 and #3, which fall below the target. The penalty values are determined based on an approach derived from Eco-indicator 99. Following this, the weighting of each sustainability KPI is performed, with weights assigned by the user. Methods such as the Delphi method or AHP can be utilized for this purpose. This process facilitates the calculation of the SSIS (Serafim Silva et al., 2024).

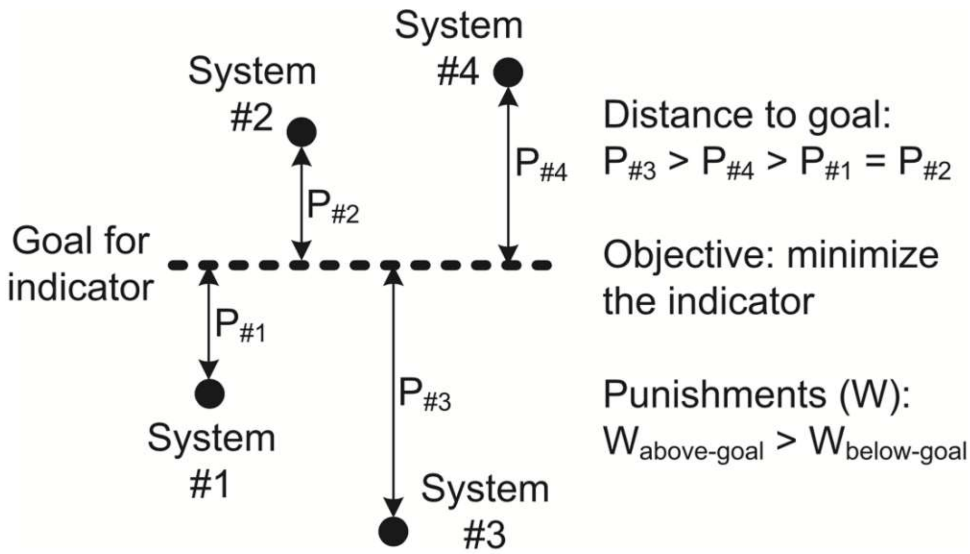

Figure 25: Philosophy of goal programming (Serafim Silva et al., 2024)

Next, improvement strategies are formulated and consolidated into Kaizen projects. Consequently, SSIS for each Kaizen project is calculated for the future state map. Since different Kaizen projects lead to varying SSIS values, a decision must be made regarding which project to implement. In addition to the SSIS values, the benefit-cost ratio (B/C) and full-time equivalent (FTE) indicators are also required for selecting the optimal Kaizen project. The decision-making process can be visually supported by representing SSIS, B/C, and FTE in a cube figure, as shown in Figure 26, which aids in the selection of the most effective Kaizen project (Serafim Silva et al., 2024).

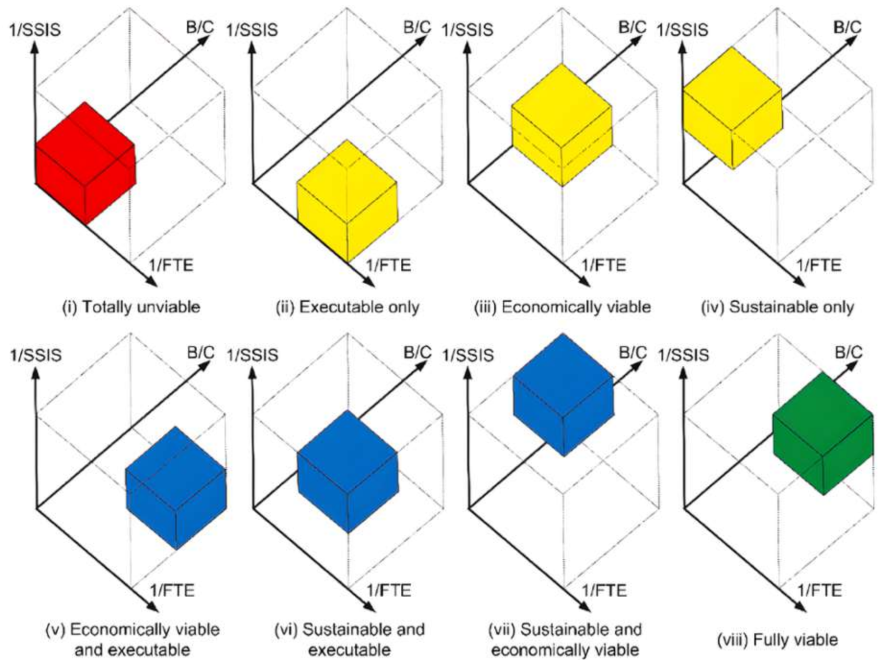

Figure 26: Eight possible scenarios for the 5SEnSU future-state VSM4S (Serafim Silva et al., 2024)

Finally, the most effective Kaizen project regarding SSIS, B/C and FTE is implemented to achieve the desired future state of the production system (Serafim Silva et al., 2024).

While VSM4S integrates economic, environmental, and social dimensions to assess sustainability, Environmental VSM narrows the focus specifically to the environmental aspects of the value stream.

Environmental VSM

Environmental VSM (EVSM) is an extension of the traditional VSM methodology, specifically focusing on the environmental dimensions of a value stream. The primary objective of EVSM is to evaluate the environmental performance of production processes and identify opportunities for mitigating ecological impacts (Li et al., 2017). This is accomplished through the analysis of material and information flows, thereby making the environmental consequences across different stages of the value stream visible (Litos et al., 2017). Consequently, EVSM incorporates both economic and environmental KPIs. According to (Litos et al., 2017), EVSM consists of five distinct phases, as depicted in Figure 27.

Figure 27: Phases in EVSM, adapted from (Litos et al., 2017)

The initial phase of EVSM involves the visualization of production steps through the mapping of material and information flows. Subsequently, the second phase focuses on defining the parameters and performance dimensions necessary for assessing of environmental impacts (Litos et al., 2017). The third phase involves the calculation of the environmental impacts of each production step using LCA software and then integrated into the EVSM. In the use case documented by (Litos et al., 2017), the LCA results are validated by comparing them against threshold values established by the European Resilient Flooring Manufacturers' Institute (ERFMI). This benchmarking enables the identification of sustainability bottlenecks and potentials within the production system. In the final phase, improvement initiatives are defined, and their potential impacts on the environmental footprint are evaluated through LCA software, facilitating the identification of strategies for reducing environmental impacts across the value stream (Litos et al., 2017).

A method for the visualization of the sustainability bottlenecks and potentials is the Sustainability Cockpit (SC), as proposed by (Li et al., 2017) and (Horsthofer-Rauch et al., 2024). Production data are integrated into SC and subsequently visualized using a Sankey diagram, as illustrated in Figure 28. The Sankey diagram is generated via an EVSM Sankey generator and is presented to the user through and Microsoft Excel-based user interface (Li et al., 2017).

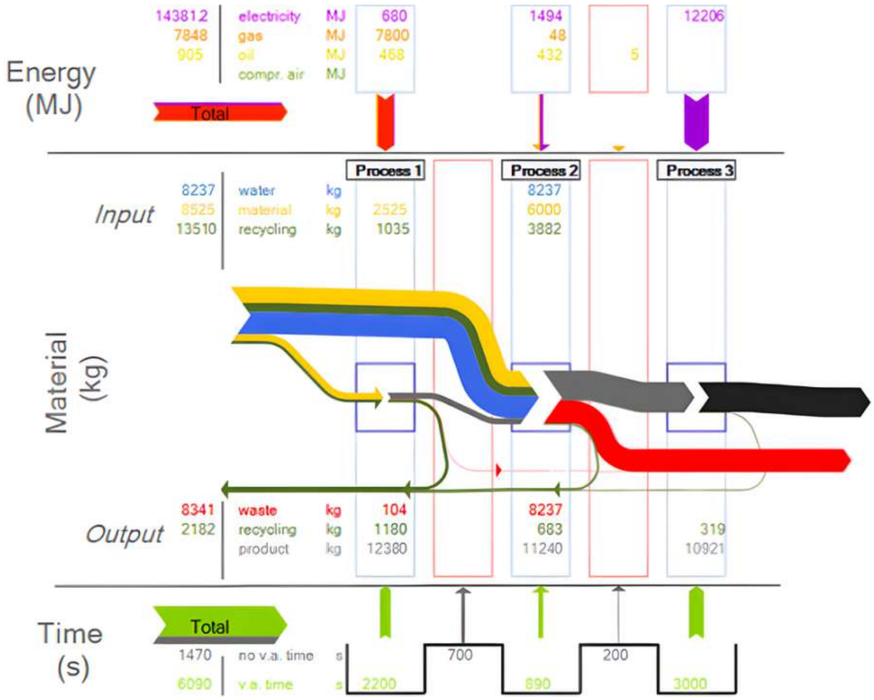

Figure 28: Sankey diagram (Li et al., 2017)

The primary advantage of a Sankey diagram lies in its ability to depict real-time data from the current state map of a value stream, while also enabling the evaluation and visualization of simulated scenarios, including what-if analyses. In this context, only economic and environmental KPIs are considered, which may encompass energy consumption, material usage, value-added time, and non-value-added time. The flow direction within the diagram is represented by arrows, where the width of the arrows corresponds to the quantity of the flow. This graphical representation allows users to pinpoint which work steps have the most significant environmental impact, facilitating targeted sustainability improvements (Li et al., 2017).

Building on the environmental focus of EVSM, the Green-Integrated VSM (GIVSM) further refines the methodology by adding lean principles, which helps identify sustainability bottlenecks and opportunities across both economic and environmental dimensions.

Green-Integrated VSM

Green-Integrated VSM (GIVSM) is a methodology that extends traditional VSM by incorporating lean and green aspects to identify sustainability bottlenecks and potentials (Choudhary et al., 2019). The phases of GIVSM are illustrated in Figure 29.

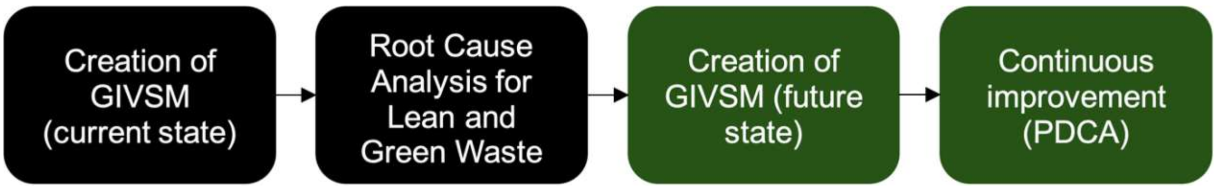

Figure 29: Phases in GIVSM, adapted from (Choudhary et al., 2019)

The first phase involves the visualization of GIVSM for the current state, utilizing data on material and information flows to identify various types of lean and green wastes and incorporating sustainability KPIs. This approach encompasses only economic and environmental KPIs. According to (Choudhary et al., 2019), besides the seven Lean Wastes, the seven Green Wastes are defined. These include waster of energy, water, and material, garbage, transportation, emissions, and biodiversity. Most of these wastes can be quantified in terms of total GHG emissions, which are expressed as CO_2e (Choudhary et al., 2019).

For the analysis of lean and green wastes, (Choudhary et al., 2019) propose the application of Root Cause Analysis for Lean and Green Waste, aimed at developing strategies to enhance efficiency and reduce the environmental impact of the production processes. The subsequent phase in GIVSM involves the creation of a GIVSM for the future state, which incorporates the implementation of the proposed improvement initiatives. Finally, these initiatives should be supported by a continuous Plan-Do-Check-Act (PDCA) – cycle, to ensure the long-term sustainability and effectiveness of the GIVSM framework (Choudhary et al., 2019).

In addition to GIVSM, another methodology that similarly addresses both economic and environmental KPIs is Circular VSM, which incorporates the principles of Circular Economy into value stream mapping. This approach emphasizes the optimization of resource flows and the reduction of waste, aligning with the core objectives of sustainability.

Circular VSM

Circular VSM (CVSM) is a methodology designed to visualize value streams by integrating Circular Economy principles with Lean tools (Kalemkerian et al., 2024). As shown in Figure 30, the approach is structured into four distinct phases and primarily focuses on assessing economic and environmental KPIs.

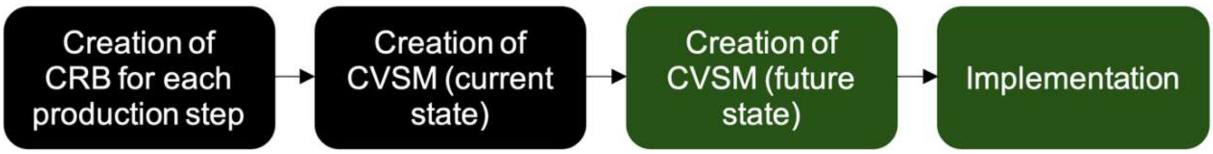

Figure 30: Phases in CVSM, adapted from (Kalemkerian et al., 2024)

In order to enhance the sustainability performance of an organization, CVSM employs the concept of the "Circular Resource Box (CRB)", which provides a clear and structured representation of resources and wastes associated with each production process, as illustrated in Figure 31 (Kalemkerian et al., 2024).

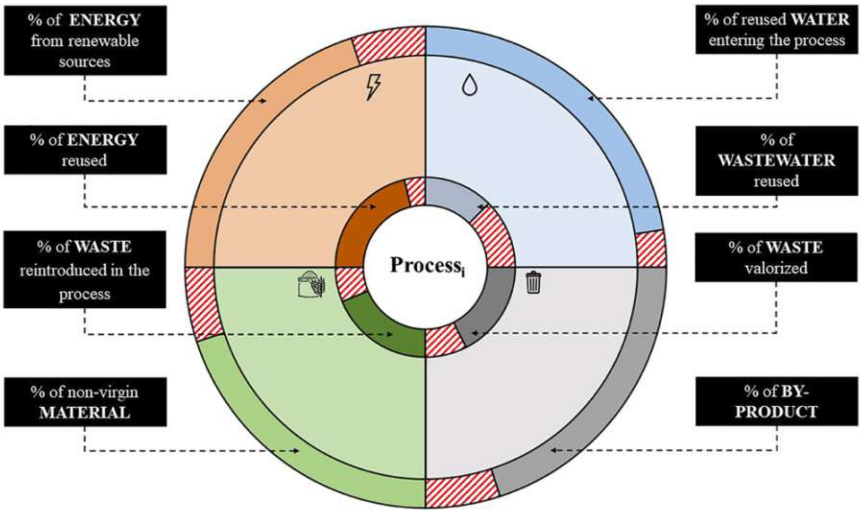

Figure 31: Circular Resource Box (Kalemkerian et al., 2024)

According to (Kalemkerian et al., 2024), the CRB encompasses categories such as energy, water, materials, by-products and waste. Each of these categories is represented by specific color codes, which can be adapted or extended depending on the specific application context. The CRB consists of two concentric circles, symbolizing potential resource flows both within and outside the organizational boundaries. For example, in the "Energy" category, the inner circle represents the portion of energy generated or sourced from various streams or flows within the process, while the outer circle reflects the utilization of renewable energy sources, such as solar, wind, and biomass. Since CRB provides qualitative information, sustainability KPIs are used for the quantitative assessment of a production step (Kalemkerian et al., 2024).

To identify potential improvements in environmental performance, it is essential to develop a current state map for the production process. CRB for each individual production step is generated, as demonstrated in Figure 32.

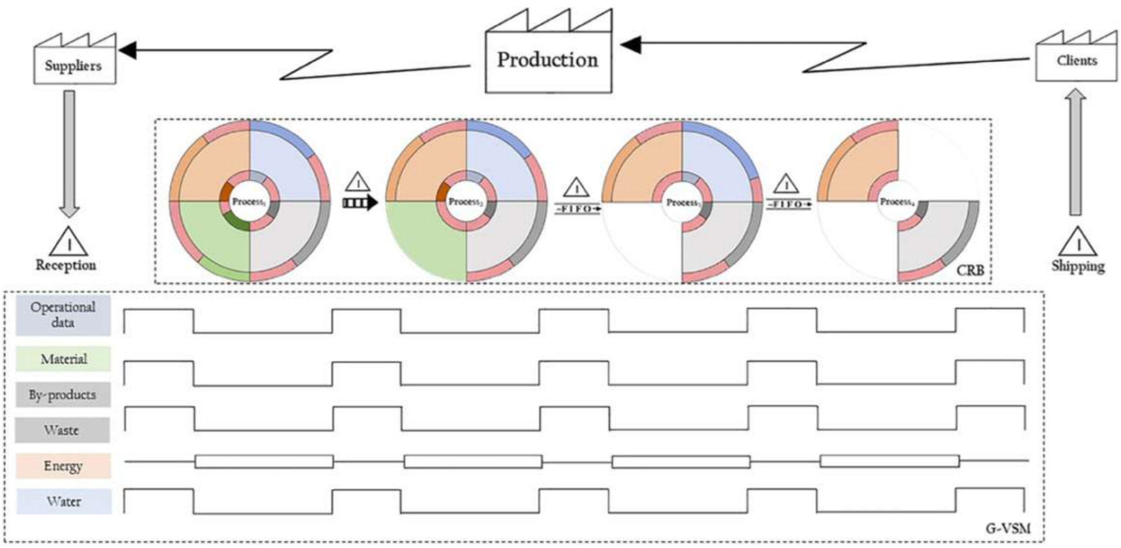

Figure 32: Circular Value Stream Mapping (Kalemkerian et al., 2024)

By analyzing each category and its associated sustainability KPIs, opportunities for improvement can be identified. Based on an assessment of the expected outcomes of proposed improvements, a future state map is then developed, outlining the potential benefits and impacts of the recommended strategies. Once the impacts of the improvement initiatives shown in the future state map are evaluated, they need to be compared with the targeted sustainability KPIs and desired outcomes. When these impacts align with the goals set, the organization can proceed with implementing the initiatives. This ensures that the planned improvements effectively contribute to the intended sustainability objectives (Kalemkerian et al., 2024).

Building upon the principles of Circular VSM, the Overall Greenness Performance (OGP) - VSM methodology also emphasizes both economic and environmental KPIs, offering a more comprehensive view of production processes and their environmental performance.

Overall greenness performance VSM

Overall Greenness Performance (OGP) - VSM is a tool for representing production processes that integrates both economic and environmental KPIs. This extended mapping approach demonstrates the interdependencies of activities and provides environmental performance-related insights. The OGP-VSM methodology encompasses five distinct phases, as illustrated in Figure 33.

Figure 33: Phases in OGP-VSM, adapted from (Muñoz-Villamizar et al., 2019)

The initial phase involves the visualization of the current state map of the value stream. According to (Muñoz-Villamizar et al., 2019), it is crucial for organizational decision-makers to define, in advance, the specific economic and environmental KPIs that will be applied throughout the mapping process. In the second phase, the identification of the seven types of Lean Management wastes is carried out by domain experts and allocated to the OGP categories, which are depicted in Figure 34.

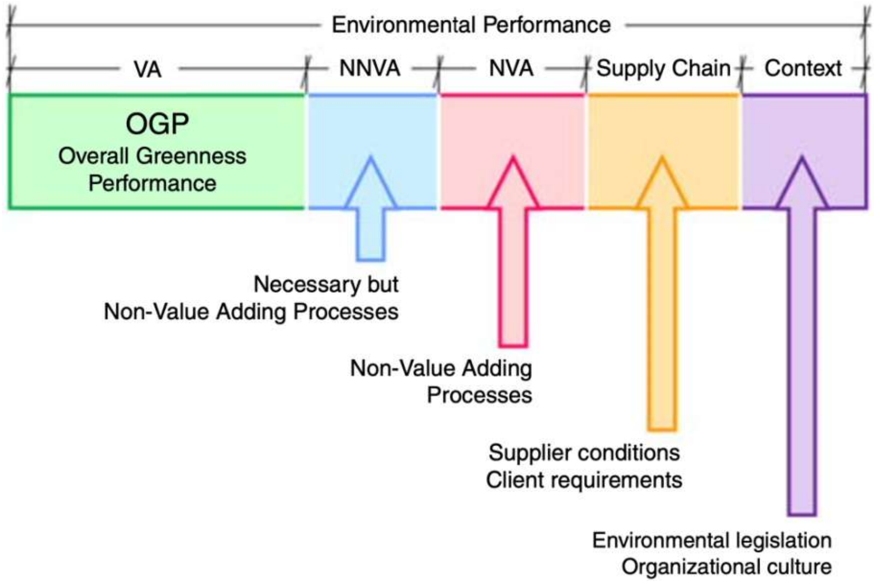

Figure 34: OGP categories (Muñoz-Villamizar et al., 2019)

In the OGP-VSM, Lean Management wastes that directly affect the environmental performance of production processes are shown with a drop icon called the "environmental burst" (Muñoz-Villamizar et al., 2019).

In the third phase, a Lean state map is created, in which improvement strategies for waste reduction are formulated. This phase only focuses on identifying and eliminating inefficiencies within the production process based on Lean Management principles (Muñoz-Villamizar et al., 2019).

Subsequently, company experts assess the proposed waste reduction strategies. The impact of these strategies on the environmental performance of the production process is evaluated using environmental KPIs, allowing for a measurable assessment of sustainability improvements (Muñoz-Villamizar et al., 2019).

In the final phase, the Lean-Green-State map is developed, which encompasses a comprehensive implementation plan that incorporates strategies for improving both economic and environmental KPIs. This phase integrates lean principles with environmental considerations to create a holistic approach for optimizing production processes (Muñoz-Villamizar et al., 2019).

Summary of the key characteristics of the methodologies

In this chapter, Table 1 summarizes the key characteristics of the methodologies identified through SLR.

Methodologies	Key characteristics
SVSM	• Integrative Approach: Incorporates economic, environmental and social dimensions • Selection of sustainability KPIs through the Delphi method and AHP • Assessment of sustainability Performance through the calculation of MSI or Overall SI • Improvement through utilization of expert knowledge and monitoring through tools like SPC and check charts
LC-VSM	• Integrative Approach: Incorporates economic, environmental and social dimensions • LC-VSM considers all stages of a product's lifecycle • Environmental impact assessment using LCA software: Quantifies environmental impacts in terms of kg CO_2e for each lifecycle phase • Improvement through the highlighting of phases with the highest and lowest environmental impacts
EVSM	• Integration of economic and environmental KPIs • Environmental impact assessment using LCA software • Validation of LCA results through benchmarking against thresholds established by ERFMI • Visualization of the environmental impacts using a Sankey diagram
TBL-VSM	• Integrative Approach: Incorporates economic, environmental and social dimensions • Incorporation of traditional Lean Management KPIs, GRI standards, SBTi, and GHG protocol for selecting sustainability KPIs • Waste Assessment and Improvement Identification: Focuses on analyzing waste in production processes and identifying opportunities for improvement
GIVSM	• Focus on economic and environmental KPIs • Definition of the seven green wastes • Utilizes the Root Cause Analysis for enhancing efficiency and reducing environmental impact • Continuous Improvement Cycle to ensure the ongoing sustainability and effectiveness of the GIVSM
CVSM	• Combines Circular Economy concepts with Lean tools to visualize and optimize value streams • Utilizes Circular Resource Box (CRB) for the structured representation of resources and wastes • Assessment of the sustainability Performance through economic and environmental KPIs
OGP-VSM	• Integration of economic and environmental KPIs • Lean-Green-State Mapping: Integrates both Lean principles and environmental considerations into a comprehensive improvement plan for sustainable production

Methodologies	Key characteristics
	• Environmental Strategy Assessment: Evaluates strategies for reducing environmental wastes by analyzing their effectiveness through environmental KPIs
VSM4S	• Integrative Approach: Incorporates economic, environmental and social dimensions • Relies on the 5SEnSU model and goal programming philosophy • Assessment of sustainability Performance through the calculation of $SSIS$ • Decision-Making Framework: Uses SSIS, benefit-cost ratio (B/C), and full-time equivalent (FTE) indicators to select the optimal Kaizen project

Table 1: Key characteristics of the methodologies

After providing an in-depth explanation of the methodologies employed in this work, it is essential to explore the application areas of these approaches. Understanding where these methodologies are applied offers valuable insights into their practical relevance and effectiveness across various sectors.

4.2.2 Application Domains of Sustainability Assessment Methods

Figure 35 provides a detailed overview of the distribution of applications across various industries. The Automotive Industry ranks first with ten publications, of which nine utilize SVSM, while one explores the use of OGP-VSM. Close behind are the Mechanical Engineering & Manufacturing sector and the Food Production sector, each with seven publications, predominantly focused on SVSM and LC-VSM.

The Metals and Plastics sector contribute five publications, while the Wood and Furniture sector contributes four publications, all utilizing SVSM to assess the sustainability performance of production systems. In comparison, the Construction Materials and Renewable Energy & Environmental Industries sectors have three publications each, with SVSM usage notably prevailing in the Renewable Energy & Environmental Industries sector.

The Consumer Goods and Apparel sectors is represented by two publications addressing sustainability, along with one publication presenting concepts without specifying particular application areas. Finally, the Pharmaceutical and Chemicals Industry and the Packaging and Labelling Industries each contribute one publication focusing on sustainability in production systems.

A clear trend emerges across industries, showing that SVSM is the dominant methodology in most sectors. In contrast, other methodologies tend to be more industry specific. LC-VSM appears mainly in the Food Production and Mechanical Engineering & Manufacturing sectors. EVSM is applied in Renewable Energy & Environmental Industries and Construction Materials. TBL-VSM and GIVSM are observed in the Pharmaceutical and Chemical sector and the Packaging & Labelling Industries, respectively. This indicates that SVSM represents a widely adopted methodology across multiple industries, while other VSM variants are applied in a more targeted manner to accommodate specific sustainability objectives or industry-specific constraints.

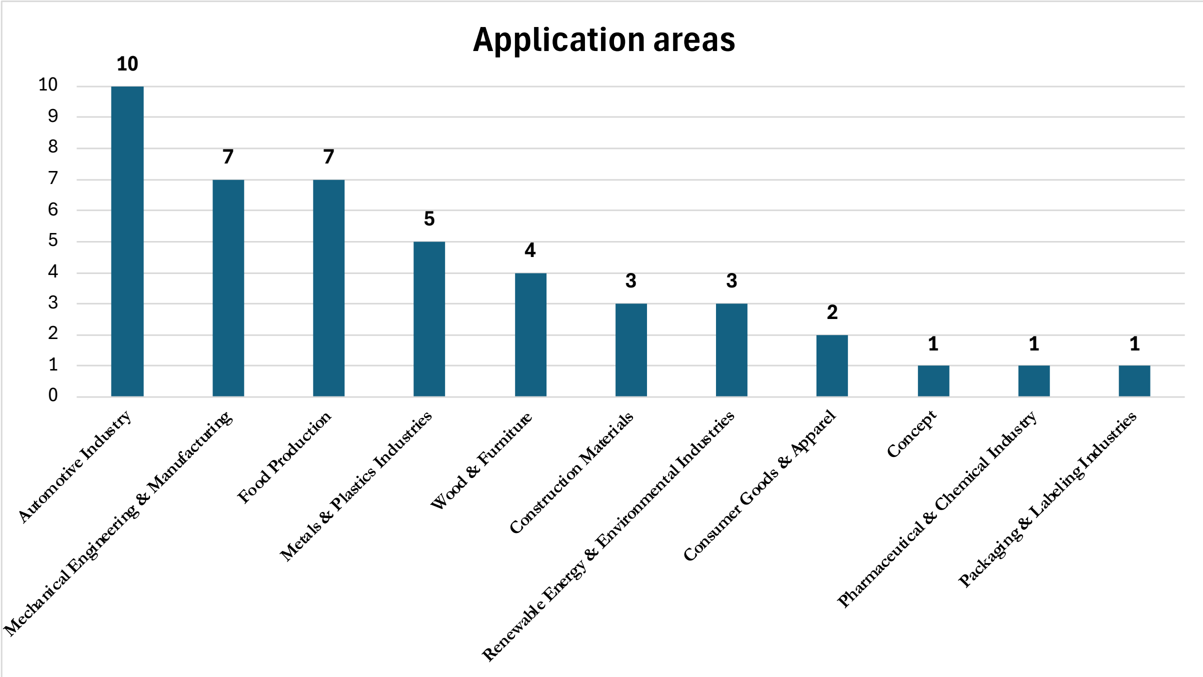

Figure 35: Identified application areas through SLR

Building upon the insights from the application areas, it is crucial to investigate the data collection methods employed within these industries. A comprehensive understanding of how data is systematically gathered and analyzed provides a deeper perspective on how effectively the methodologies are applied and their relevance to the specific sustainability objectives of each sector.

4.2.3 Data Sources and Acquisition in Sustainability Assessment Methods

A fundamental prerequisite for assessing sustainability performance in production systems is the availability of relevant and reliable data. Across all sectors, most studies rely on primary data obtained through direct observations, measurements at the shop floor level, or discussions with stakeholders. In several publications, case studies were conducted within each sector to contextualize and analyze sustainability practices. For instance, (Swarnakar et al., 2020), (Swarnakar et al., 2021) and (Marie et al., 2022) in the automotive sector, (Helleno et al., 2017) in the metals and plastics industries and (Kalemkerian et al., 2024) in the food production sector collected data through direct observation and interaction with company personnel, a practice mirrored by (Sari et al., 2022) and (Jamil et al., 2020) in the metals and plastics industries.

In the domain of construction materials production, (Litos et al., 2017) and (Salvador et al., 2021) evaluated the environmental impacts of production processes using LCA. Due to the comprehensive and cross-system nature of Life Cycle Assessment, these studies rely on external databases to obtain consistent and comparable inventory data. External databases are typically used in LC-VSM to provide consistent and comprehensive data across all life cycle phases. Especially, (Litos et al., 2017) employed the LCA software “GABI by Thinkstep”, while (Salvador et al., 2021) utilized data from the “Ecoinvent” database. Similarly, in the mechanical engineering and manufacturing sector, (Samant & Prakash, 2020) analyzed the environmental impacts derived from the LCI (mass and energy flows) to assess the overall Life Cycle Environmental Impact, utilizing the “lcacalculator” tool, which incorporates data from the “Ecoinvent” database.

For instance, (Lindström & Ingesson, 2016) and (Ferrazzi & Portioli-Staudacher, 2023) in the automotive sector, (Soltani et al., 2019) in the metals and plastics industries and (Antomarioni et al., 2018) all assessed energy consumption at the machine level and material consumption based on process and product data. Similarly, (Hartini et al., 2018) in the wood and furniture industry analyzed material input-output balances and theoretically calculated the material consumption.

Several studies also used mathematical calculations and formulas to derive sustainability metrics, such as the work by (Edtmayr et al., 2016) in the automotive sector. Furthermore, (Vinodh et al., 2016) examined noise levels and water usage during machining processes in the automotive industry, while (Lindström & Ingesson, 2016) evaluated ergonomic conditions in the same sector. Similarly, (Hartini et al., 2019) analyzed ergonomic conditions in the food production sector using the method “Rapid Entire Body Assessment (REBA)”.

According to (Phuong & Guidat, 2018), in the consumer goods and apparel sector, data collection is conducted through time studies or by calculating the process cycle time. Inventory levels are updated daily to ensure real-time accuracy and effective resource management. For environmental and social KPIs, theoretical values are calculated, while actual data is measured for validation. The available data used in these assessments is provided directly by production management, ensuring reliability and alignment with operational practices.

Similarly, in the metals and plastics industries, (Jamil et al., 2020) conducted direct measurements on machines, assessing energy, water, and chemical consumption, as well as noise levels, while (Li et al., 2017) in the renewable energy & environmental industry, estimated the power rate of each process based on the rated power and experts experiences.

Building on the insights from data collection, the following section delves into the specific sustainability dimensions that are addressed in the literature. This examination provides a deeper understanding of how these dimensions are integrated into the assessment of sustainability performance across different sectors.

4.2.4 Sustainability Dimensions in Assessment Methods

Figure 36 illustrates the frequency of the sustainability dimensions considered in the relevant publications. A total of 30 publications incorporates all three dimensions of sustainability to visualize and evaluate the performance of production systems. In contrast, 14 publications focus solely on the economic and environmental dimensions. This observation suggests that, despite the principles of the Triple Bottom Line advocating balanced consideration of economic, environmental, and social aspects, some literature still tends to prioritize economic and environmental criteria, while social dimensions receive comparatively less attention.

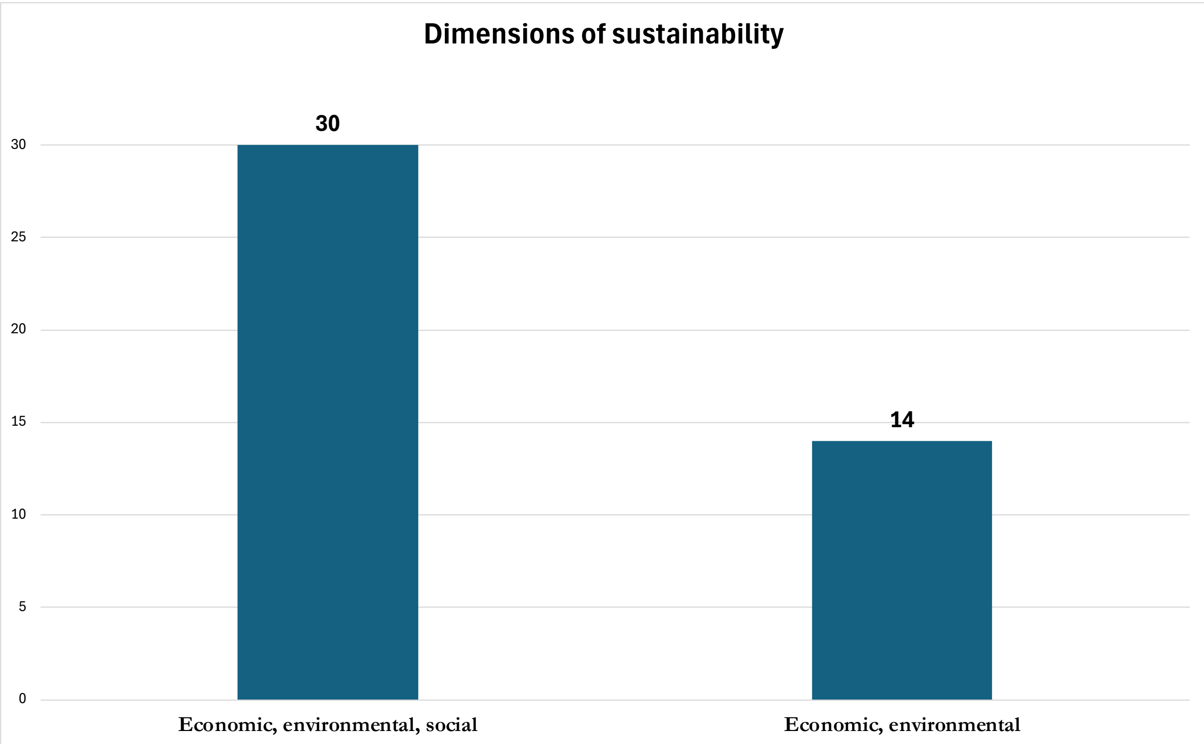

Figure 36: Considered dimensions of sustainability in the relevant publications

The assessment of sustainability in different industries shows interesting differences and similarities. Most publications refer to the TBL framework, which analyzes the economic, environmental and social KPIs to assess sustainability performance. While the importance of the economic dimension is generally recognized, the relative weighting of the individual TBL pillars varies within different companies.

The relative importance of sustainability KPIs is intrinsically tied to a company's strategy and sustainability goals. Organizations prioritize different dimensions of the TBL based on their overarching objectives and the challenges they face within their industry. For instance, in the case studies which are conducted in the automotive industry, economic factors dominate, while environmental KPIs receive little attention (Sari Emelia et al., 2021) and (Marie et al., 2022). In the study conducted by (Marie et al., 2022), social KPIs have a relative importance of 44%, indicating a high priority after economic factors. On the other hand, (Dewi et al., 2023), (Ferrazzi & Portioli-Staudacher, 2023), (Lindström & Ingesson, 2016) and (Vinodh et al., 2016) present a contrasting perspective. (Dewi et al., 2023) assign equal importance to all three TBL dimensions (each 33.3%), whereas (Ferrazzi & Portioli-Staudacher, 2023), (Lindström & Ingesson, 2016) and (Vinodh et al., 2016) primarily focus on improving environmental KPIs.

In the case study conducted by (Hudy et al., 2023) in the mechanical engineering and manufacturing industry, the relative importance of economic, environmental, and social KPIs is 50%, 22%, and 28%, respectively, indicating that environmental and social factors remain secondary to economic considerations. Due to the lower importance of environmental aspects, this dimension performs poorly, while social KPIs perform better. According to (Ikatrinasari et al., 2018), the case study focused on economic and environmental KPIs, specifically electrical energy consumption. (Khakpour et al., 2023) take all three sustainability KPIs into account. However, the experts in the case study primarily focus on economic factors by developing improvement strategies specifically to enhance economic KPIs. Nevertheless, these measures also positively influence environmental and social KPIs.

In the metals and plastics industry, (Sari et al., 2022), (Mubin et al., 2023), and (Soltani et al., 2019) analyze case studies that all consider economic, environmental, and social KPIs. However, their results differ in terms of the relative importance of each dimension. (Soltani et al., 2019) report a distribution in which economic KPIs are more important (49%) than environmental KPIs (26%) and social KPIs (25%). In contrast, (Mubin et al., 2023) find a much stronger emphasis on economic factors (54%), followed by social (30%) and environmental (16%) considerations. Despite the relatively high importance of social KPIs, their study points to inefficiencies in the social dimension, indicating the greatest need for improvement. (Chaparin et al., 2023) concentrate exclusively on economic and environmental KPIs within the food production sector, emphasizing the significance of these two dimensions.

In the case study conducted by (Larsson & Ratnayake, 2024) in the renewable energy and environmental industry, environmental factors are assigned significantly greater importance compared to most other sectors, with a relative importance of 31.1%. In contrast, the economic and social dimensions are assigned relative importance values of 49.3% and 19.6%, respectively.

According to (Marie Iveline Anne et al., 2022) and (Utama et al., 2022), the consumer goods and clothing industry as well as the wood and furniture industry, largely reflects the trend observed in the automotive sector, where economic factors are the main focus, accounting for approximately 65-70% of relative importance, followed by environmental (17-25%) and social (7-9%) considerations. Consequently, the social KPIs in the case studies exhibit a relatively low efficiency score, indicating a need for immediate action.

In conclusion, the assessment of sustainability across industries reveals both notable differences and shared patterns in the application of TBL framework. While the economic dimension is generally prioritized, the weighting of environmental and social KPIs varies significantly, reflecting each company’s strategic focus and the unique challenges within its industry.

Building on the assessment of sustainability KPIs across industries, the following section presents how these indicators are used to identify specific sustainability bottlenecks and potentials. This process is essential for pinpointing areas where improvements can be made, ultimately enhancing the sustainability performance of production systems.

4.2.5 Identification of sustainability bottlenecks and potentials

In this section, the methods employed for identifying sustainability bottlenecks and potentials in production systems are examined. The bar chart presented in Figure 37 illustrates these methods and their respective frequencies. The most prevalent approach is the application of expert knowledge, referred to as the " Expert- and Lean-based Methods" in the chart. The second most utilized method involves the "Defining of Critical Target Values for Sustainability KPIs" while “Algorithmic Approaches” are also applied to identify sustainability bottlenecks and potentials within production processes. It is noteworthy that five publications do not address sustainability aspects.

In the following, a more detailed discussion of the methods used to identify sustainability bottlenecks and potentials will be provided.

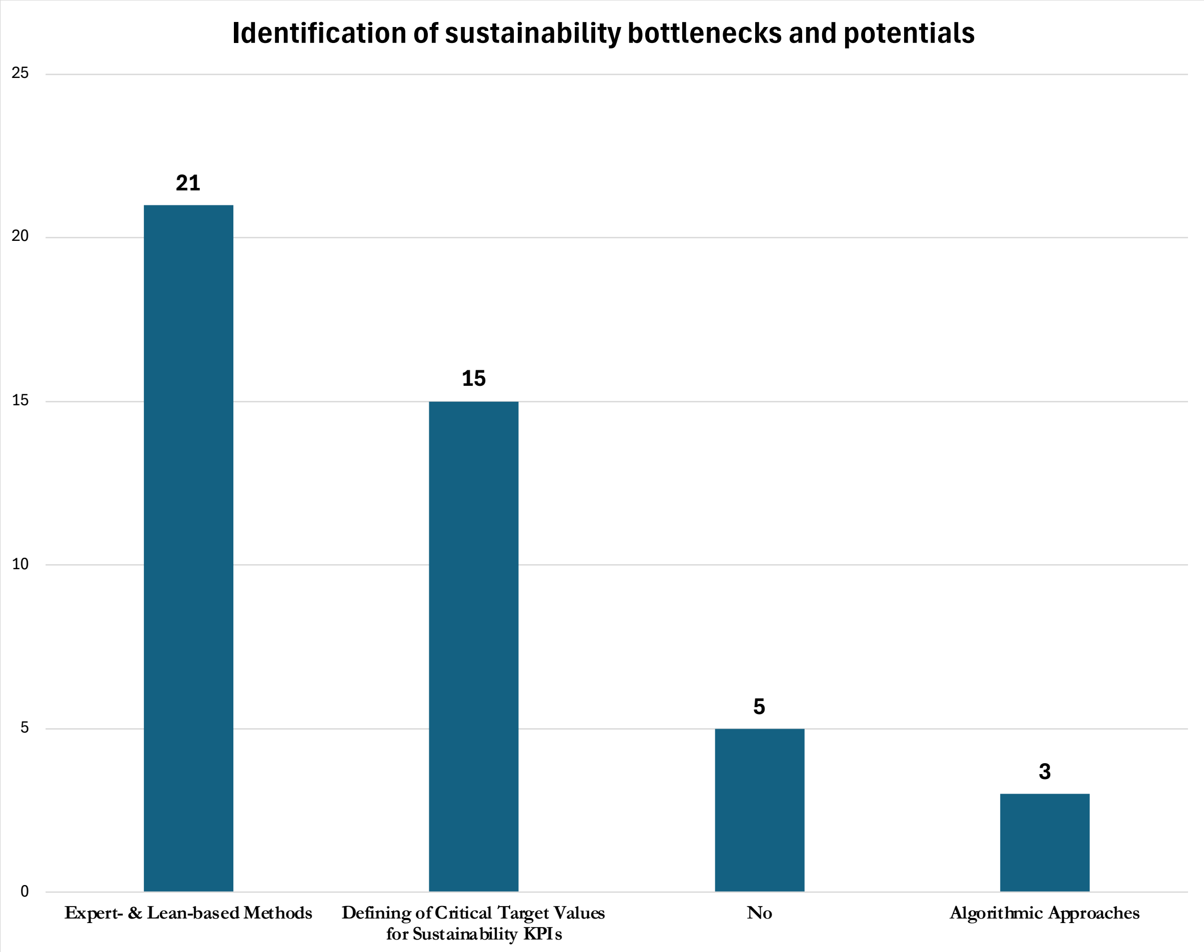

Figure 37: Frequency of methods for the Identification of sustainability bottlenecks and potentials in production systems

Expert- and Lean-based Methods

Expert knowledge and lean-based methodologies play a central role in identifying inefficiencies and enhancing sustainability performance in production systems. To this end, a variety of approaches grounded in expert judgment and traditional lean tools have been applied across different studies. Kaizen actions, including 5S, TPM, SMED, and Poka Yoke, are frequently implemented to address inefficiencies in processes and to optimize resource usage.

These actions, supported by expert judgment and analysis of historical data, not only reduce nonvalue-adding activities but also contribute to environmental and social KPIs, particularly by lowering resource consumption, energy usage, waste generation, and improving PLI scores (Antomarioni et al., 2018), (Chaparin et al., 2023), (Swarnakar et al., 2021) and (Vinodh et al., 2016). Additionally, (Salvador et al., 2021) emphasizes the 5W method in Kaizen action planning, which ensures that improvement measures specifically target sustainability-related inefficiencies. Similarly, (Ikatrinasari et al., 2018) explore how lean tools like SMED can reduce environmental inefficiencies, particularly in energy usage, by categorizing electrical consumption in production processes. The implementation of lean practices such as Gemba Walks, Kanban systems, and supermarket pulling further underscores the role of lean methodologies in optimizing sustainability performance (Khakpour et al., 2023).

Root cause analysis tools, like Fishbone Diagrams and FMEA, have been utilized to identify inefficiencies and propose corrective measures (Choudhary et al., 2019), (Sari et al., 2022), (Utama & Abirfatin, 2023) and (Djatna & Prasetyo, 2019). For example, (Choudhary et al., 2019) defined seven green wastes alongside traditional lean waste, providing a novel perspective for identifying environmental inefficiencies. Similarly, (Hartini et al., 2019) utilize the type of waste, cause and effect approach for identifying inefficiencies and implementing corrective measures. Furthermore, (Muñoz-Villamizar et al., 2019) emphasizes the integration of green waste into VSM, utilizing drop symbols to mark inefficiencies. These efforts ensure targeted improvements in sustainability and lean outcomes.

Incorporating sustainability KPIs into the current state SVSM enables experts to assess inefficiencies in the value stream based on their knowledge and experience. Additionally, experts apply lean tools to develop a scenario for the future state map, outlining targeted measures to improve efficiency and sustainability in the production process (Phuong & Guidat, 2018), (Kluczek & Bartlomiej, 2020) and (Hartini et al., 2018). Statistical Process Control (SPC) tools, for instance, enable monitoring and controlling critical parameters to ensure sustained improvements (Jamil et al., 2020).

The integration of visual tools, such as Sankey diagrams and CRB, further facilitates the identification and reduction of resource-intensive processes (Li et al., 2017) and (Kalemkerian et al., 2024). These methods enable experts to pinpoint inefficiencies and propose targeted measures. Furthermore, (Samant & Prakash, 2020) uses LCIA to identify environmentally high-impact production processes and ultimately recommending improvement initiatives.

According to (Saraswati et al., 2024), the 3R analysis (reuse, reduce, recycle) can also be used to emphasize sustainability aspects. It helps make processes not only more efficient but also more environmentally friendly, integrating lean practices with sustainability goals. Interdisciplinary approaches leveraging expert interviews and collaborative analysis have also been instrumental. For instance, (Chavez et al., 2023) emphasize the improvement of GRI 306 and 403 KPIs through systematic evaluation of historical data.

Overall, these studies highlight the critical role of expert knowledge combined with innovative tools in enhancing sustainability, reducing waste, and fostering continuous improvement in production processes.

While expert- and lean-based methods are used to identify sustainability bottlenecks and potentials, another key approach is the establishment of target values for sustainability KPIs.

Defining Critical Target Values for Sustainability KPIs

To systematically manage and improve sustainability performance within value streams, it is crucial to define critical target values for sustainability KPIs. These targets provide benchmarks that help identify inefficiencies and guide improvement initiatives. According to (Antomarioni et al., 2018), (Phuong & Guidat, 2018), (Hartini et al., 2020), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Utama et al., 2022), (Utama & Abirfatin, 2023), (Hudy et al., 2023), (Dewi et al., 2023), (Mubin et al., 2023) and (Rosiani et al., 2024), all publications employed TLS within SVSM to systematically visualize inefficiencies and facilitate decision-making. This approach enhances analytical precision by visually representing critical KPIs, thereby helping to prioritize areas for improvement. The selected sustainability KPIs were calculated to determine efficiency based on the formula provided in Table 7.

By employing TLS, sustainability performance levels are indicated with red, yellow, and green colors. According to (Hartini et al., 2020) and (Marie Iveline Anne et al., 2022), the color coding for critical efficiency values varies based on the capacity level and company policy. According to (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Hudy et al., 2023), (Utama & Abirfatin, 2023), (Dewi et al., 2023), (Mubin et al., 2023) and (Rosiani et al., 2024), the color red indicates manufacturing efficiency values below 60%, the color yellow represents efficiency values between 60% and 90%, and the color green signifies that the efficiency exceeds the set target, which is above 90%. However, (Marie et al., 2022) defined the color red for values below 65%, the color yellow for values ranging from 66% to 89%, and the color green for values between 90% and 100%.

The color red indicates that the performance of the sustainable manufacturing indicator needs to be improved immediately. The color yellow denotes that the attained value is suboptimal and requires further improvement. The color green signifies that the indicator value meets the established target. This visual methodology facilitates the rapid assessment and communication of sustainability performance status, thereby enabling timely and informed interventions as necessary (Hartini et al., 2020).

According to (Antomarioni et al., 2018), TLS is used in every step of the process to show the amount of CO_2 released. The color green indicates values below 30 gCO_2/1000pz, the color yellow represents values ranging from 30 gCO_2/1000pz to 120 gCO_2/1000pz, and the color red corresponds to values above 120 gCO_2/1000pz. According to (Phuong & Guidat, 2018), the generation of green waste in a production process is also illustrated using TLS, providing a clear visualization of risk levels associated with waste management. TLS employs a color-coded legend to indicate the degree of risk. The color red signifies "dangerous", representing hazardous green waste that poses significant risks, the color “yellow” denotes "alert", indicating waste that requires caution and monitoring, and the color “green” signifies "safe", representing waste deemed non-harmful and manageable within standard practices. This visualization facilitates an effective risk assessment of green waste, enabling decision-makers to identify critical areas and implement strategies for improved sustainability and safety in the production process.

Furthermore, (Litos et al., 2017) and (Helleno et al., 2017) compare the sustainability KPIs with target values determined by production leaders and HR experts or predefined European industry performance levels in order to identify inefficiencies in the production process.

Building on the establishment of target values for sustainability KPIs, algorithmic approaches present an advanced methodology to further streamline decision-making processes regarding sustainability aspects in production systems.

Algorithmic Approaches

Various algorithmic methods have been developed to support the assessment of sustainability in manufacturing, enabling the identification of critical processes and the ranking of production steps and improvement initiatives based on their impact on environmental, social, and economic KPIs. For the purpose of sustainability assessment in manufacturing, (Soltani et al., 2019) conducted an empirical study within the metal industry, examining the production process of gas bottles. In their approach, the TOPSIS algorithm was employed to rank individual manufacturing operations according to their contribution to the overall process sustainability. The determination of the relative importance of the sustainability-related KPIs was carried out using the AHP methodology. The analysis resulted in a ranked list of production steps, providing insights into which operations exert the most significant influence on the sustainability performance of the overall manufacturing system.

Another methodological approach was presented in the study by (Aouag & Soltani, 2023). In this work, the weights of the sustainability KPIs were determined using Shannon's Entropy Method, an objective weighting technique based on the dispersion of data. The primary objective of the study was to evaluate the effectiveness of various Lean tools, including Kanban, 5S, TPM, SMED, in improving sustainability performance.

To perform the multi-criteria evaluation, the authors applied both the fuzzy EDAS method and the fuzzy TOPSIS algorithm. The comparative analysis showed a very high correlation between the ranking results generated by fuzzy EDAS and fuzzy TOPSIS, regardless of the type of weighting technique applied. This consistency confirms the robustness of the chosen methodological framework and reinforces the credibility of the sustainability-oriented evaluation of Lean interventions (Aouag & Soltani, 2023).

Another approach to assessing the sustainability performance of a value stream was presented by (Serafim Silva et al., 2024). The VSM4S methodology applies a goal programming-based algorithm to quantitatively evaluate sustainability by integrating economic, environmental, and social dimensions through selected KPIs. The algorithm begins with the identification and calculation of relevant KPIs, each assigned specific targets, penalties for deviations, and weights reflecting their importance. Deviations from targets are penalized according to goal programming principles, distinguishing whether an indicator should be minimized or maximized. These penalized deviations are aggregated into a Synthetic Sustainability Indicator of the System (SSIS), providing a comprehensive KPI for current and future sustainability states. The algorithm further supports decision-making by evaluating various improvement initiatives (Kaizen projects) through comparison of their projected SSIS values alongside B/C and FTE indicators. This multi-criteria evaluation facilitates selecting the most effective sustainability improvement project (Serafim Silva et al., 2024).

Synthesis of the Key Findings

The review of relevant literature revealed that all identified methodologies are fundamentally based on VSM and are consistently extended to incorporate the TBL perspective. By integrating sustainability KPIs, these methodologies enable the quantitative assessment of a company’s sustainability performance. In addition, the inclusion of algorithmic approaches, such as the TOPSIS algorithm, allows the identification of improvement areas within the value stream without relying on expert judgment or predefined KPI target values. This represents a distinctive advantage, as sustainability performance can be evaluated objectively and in an automated manner. Such algorithmic frameworks, when appropriately implemented, hold the potential for cross-industry application, enabling the systematic identification of sustainability potentials within production processes. The findings of this review serve as the methodological foundation for the subsequent development of SPDA and its practical implementation.

5 Development of an Algorithm for Identifying Sustainability Potentials in Value Streams

Based on the findings of the literature review, the objective of this section is to develop an algorithm capable of automatically identifying sustainability potentials within value streams. Previous methodologies identified in the literature, such as SVSM, LC-VSM, and others, integrate sustainability KPIs to quantitatively evaluate the sustainability performance of production processes. Building on this, the SPDA can systematically detect areas for improvement and provide decision support to practitioners. This algorithm, referred to as the Sustainability Potentials Detection Algorithm (SPDA), combines the AHP methodology with the TOPSIS algorithm. The AHP methodology is used to derive consistent and rational weights for sustainability KPIs based on user input obtained through pairwise comparisons. These weights are subsequently employed by the TOPSIS algorithm to rank alternative process steps according to their relative distance from an ideal and an anti-ideal solution. The SPDA thus enables structured, scalable, and transparent decision-making, including the identification of the key KPIs that most significantly influence the sustainability performance of processes requiring improvement. Collectively, this approach provides a robust methodological foundation for assessing and enhancing sustainability performance within production systems.

On this basis, the following section specifies the functional and technical requirements for the SPDA, ensuring that the algorithm effectively translates the methodological insights into practical and actionable evaluations of sustainability performance.

5.1 Requirements

The subsequent section defines the essential functional and technical specifications of SPDA. These specifications ensure that SPDA can systematically process input data, derive criteria weights, perform multi-criteria evaluations, and generate actionable insights to identify sustainability potentials within production processes.

- **Prioritization of sustainability KPIs:**
  The algorithm must be capable of prioritizing sustainability-related criteria based on their relative importance, in alignment with the organization’s strategic objectives. It should allow users to express their preferences between different sustainability KPIs in a structured and transparent way. Additionally, the system must assess the consistency and reliability of user inputs and inform users when revisions are needed to ensure valid and meaningful prioritization results. The outcome of this prioritization process shall serve as input for the overall decision-making mechanism within the algorithm.

- **Identification of sustainability potentials within Value Streams:**
  The algorithm must be capable of identifying sustainability potentials within production value streams based on quantitative KPI data. The analysis shall deliver robust, interpretable, and decision-supportive results, regardless of the specific weighting configuration applied to the sustainability KPIs. To reflect user-defined strategic priorities, the algorithm must allow users to specify the desired direction of improvement (e.g., maximization or minimization) for each KPI. Based on this classification, the algorithm should determine the relative sustainability performance of each process step and provide a comprehensible ranking of all evaluated processes. The results must clearly highlight which process steps deviate most from optimal sustainability performance, enabling users to identify and prioritize critical areas for targeted improvement. Furthermore, the algorithm shall indicate which KPIs most significantly influence the performance of each process, supporting users in conducting focused and effective optimization efforts. In addition, for processes that do not lie on the main production path but are part of an alternative path (e.g., involving rework or refinement), the algorithm must display the corresponding Path Factor. This factor serves as a decision-support metric that helps interpret the sustainability performance of processes in a structured and user-comprehensible way.
- **Integration, Maintainability, and Extensibility:**
  The solution must be designed in a modular, maintainable, and platform-independent manner. It shall support dynamic adjustments to both the number of evaluation criteria (e.g., sustainability KPIs) and the number of production processes to be analyzed. Adding or removing KPIs or processes must not require fundamental changes to the overall system architecture. The algorithm shall be scalable to accommodate large numbers of process steps while ensuring user-friendly operation. Its modular design must also support future extensions and updates with minimal development effort, ensuring long-term adaptability to evolving sustainability assessment requirements and standards.
- **Transparency, Traceability, and Reproducibility:**
  The system must ensure transparency, traceability, and reproducibility of all final computational results, and document the procedures used for evaluation and prioritization. Relevant input parameters and computed outputs must be provided in a structured and accessible format, enabling users to understand and validate the results. The system shall exhibit deterministic behavior, ensuring consistent outputs for identical inputs. This is a critical requirement for reproducibility in both academic and industrial contexts.
- **Robustness:**
  The system must ensure robustness, reliability, and operational integrity through comprehensive validation mechanisms. These mechanisms shall verify the structural correctness, logical consistency, and plausibility of all input data

and intermediate computational results. Validation must include checks that confirm the completeness and correctness of evaluation criteria, input matrices, and output data to prevent computational errors and ensure reproducibility of results. The system shall enforce that subsequent computational steps proceed only if prior validations are successfully passed, thereby preventing the propagation of errors through the analysis workflow.

Building on the defined requirements, the following section introduces the conceptual framework of SPDA, detailing its methodological approach.

5.2 Concept presentation

SPDA is an integral component of the Sustainability Monitoring Platform (SMP) and provides the necessary results for further processing by other modules within SMP. The conceptual design of this integration is structured to ensure minimal user effort while maximizing automation, reproducibility, and data integrity throughout the decision-making process.

The workflow begins when users enter sustainability-related data into SMP, as illustrated in Figure 38. This data typically includes sustainability KPIs associated with various processes in the value stream, such as energy consumption, machine downtime rate, scrape rates, or cycle times. Upon data submission, an internal controller component within SMP is triggered. This controller is responsible for extracting, validating, and formatting the user-provided data into a structured JSON format. This ensures that the data adheres to the input schema required by SPDA.

Once the input JSON is generated, it is transmitted to SPDA, which operates as a backend decision-support engine. The algorithm performs a series of computational steps, and the results of this computation are encapsulated in an output JSON file containing four key elements:

- Original Input Data – Ensures traceability and allows comparison between input and result.
- TOPSIS Scores – Quantitative evaluation scores for each process, indicating their relative sustainability performance. For processes with identified improvement potential, the key KPIs significantly influencing the scores are highlighted to enable targeted optimization measures.
- CR – A numeric indicator of the reliability of the pairwise comparison judgments used in the AHP methodology.
- Explanations – Provides descriptive insights into which KPIs have a significant influence on the sustainable performance of each process and shows the corresponding Path Factor

The output JSON is retrieved by the controller and forwarded to SMP, where it becomes available for further processing by other modules. Depending on the implementation of SMP, this may include storage, visualization, or integration into broader decision-support systems.

By decoupling the user interface from the analytical engine and ensuring standardized data exchange through JSON, the overall architecture achieves a high degree of modularity, interoperability, and scalability. This modular setup ensures that the algorithm remains adaptable and can grow alongside future developments in the platform or data environment.

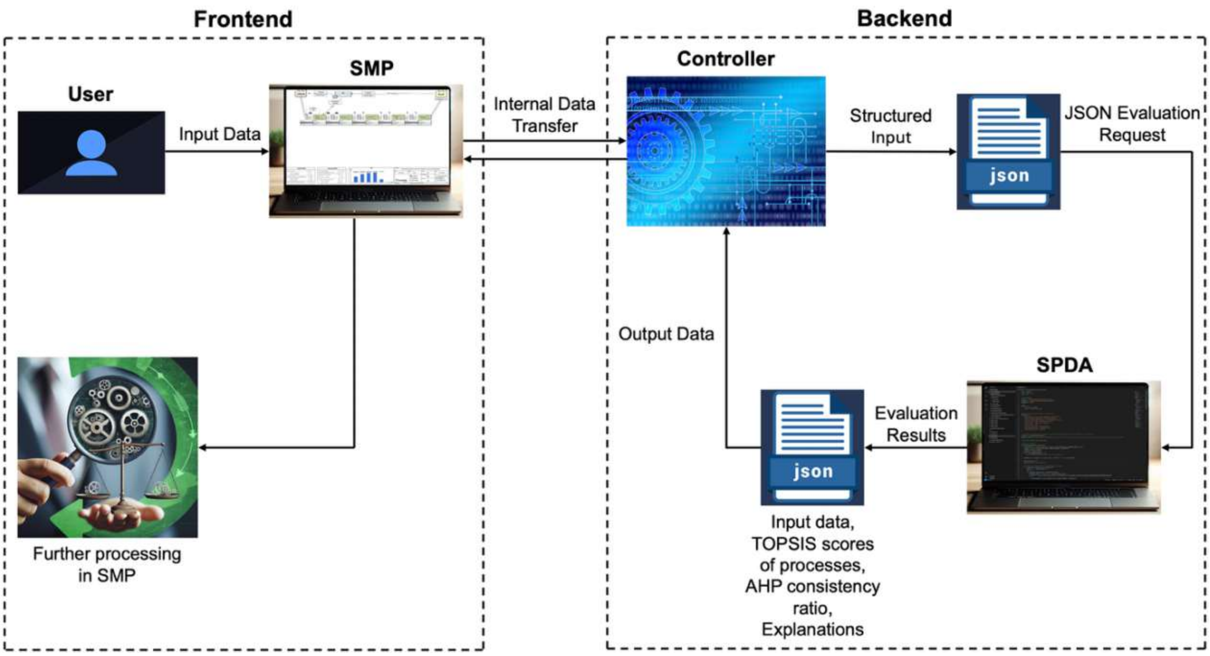

Figure 38: Conceptual framework

5.3 Proposed Approach

The subsequent chapter begins with a concise overview of the software environment used throughout the development process, including the programming language, relevant libraries, and FastAPI employed. This is followed by a detailed examination of the technical implementation of SPDA, with particular attention paid to the code structure and data flow. To enhance understanding and improve the clarity of the documentation, selected excerpts of the source code are presented. These code snippets are intended to illustrate key programming logic without overwhelming the reader with excessive detail. The objective is to provide a transparent and comprehensible representation of the algorithmic workflow while preserving the overall readability of the thesis.

Overview of the Software Environment

SPDA was developed using the Python programming language in conjunction with the Visual Studio Code development environment. Python, originally introduced in 1991 by Guido van Rossum (Hart-Davis & Hart-Davis, 2022), is a high-level, interpreted language that has gained widespread popularity due to its simplicity, readability, and broad applicability (Donaldson, 2013). It is frequently utilized in a variety of domains, including automation through scripting, data analysis, scientific computing, and web development (Donaldson, 2013). A key advantage of Python is its high degree of platform independence, as most Python scripts can be executed across all major operating systems without requiring significant modifications, thereby ensuring a high level of script portability (Lutz, 2010).

In the context of this work, the Visual Studio Code editor served as both a code editor and an integrated development environment (IDE) for authoring, testing, and debugging the Python source code (Hart-Davis & Hart-Davis, 2022). Visual Studio Code provides a wide array of extensions and features, such as syntax highlighting, code completion, version control integration, and debugging tools, which significantly enhance developer productivity and support the development of complex algorithmic workflows (Microsoft, n.d.).

Furthermore, FastAPI was employed to implement the web API interface for SPDA. FastAPI is a contemporary, high-performance web framework for building APIs with Python, leveraging standard Python type annotations to enable robust code (Ramírez, n.d.-a). Its features include automatic generation of interactive API documentation (Ramírez, n.d.-a), seamless integration with Python codebases (Ramírez, n.d.-b), and compatibility with Pydantic for data validation (Ramírez, n.d.-b). These advantages facilitate rapid development and deployment of web-based algorithms.

Following the definition of SPDA's software environment, the subsequent section presents the overall workflow, which illustrates how the system processes and analyzes input data to support sustainability assessment.

5.3.1 Workflow of SPDA

The workflow of SPDA is structured into three main phases. Each phase details the core processing steps, from data preparation and the weighting of sustainability criteria to the prioritization of production processes, as illustrated in Figure 39.

Phase 1 – Data Preparation

In the first phase, the SPDA development focuses on defining the computational workflow and ensuring that the algorithm can process input data in a structured format. The input data includes the number of processes, the number of sustainability KPIs for each process (such as energy consumption, machine downtime, scrap rates, or cycle times) along with their corresponding values, the pairwise comparison matrix, the list of benefit criterias, and the path factors.

Before applying the decision-making methodology, the input data undergoes validation to ensure structural correctness and logical consistency, including checks on matrix dimensions, reciprocal properties for AHP, and alignment of the number of KPIs with the expected input. This phase establishes the foundational structure of the algorithm and ensures that subsequent computations are robust and reproducible.

Phase 2 – Determination of criteria weights using AHP

In the second phase, the AHP approach is applied to quantify the relative importance of the selected sustainability KPIs. This begins with the normalization of a pairwise comparison matrix based on the user input, using an adapted Saaty scale to express the relative preference of one criterion over another. While this scale allows for nuanced comparisons, its complexity can pose a challenge in practical applications, particularly when involving users without prior experience with AHP.

To address this issue, the original 1–9 scale was simplified to a three-level scale in this work, aiming to enhance usability and reduce cognitive load in the decision-making process, as illustrated in Table 2.

User Input/Saaty Equivalent	Interpretation
1/3	Less important
1	Equally important
3	More important

Table 2: Adapted Saaty's scale

Following the pairwise comparison, the relative weights of each sustainability KPI is derived. A consistency analysis is subsequently performed to evaluate the logical coherence of the pairwise comparisons. Specifically, the CI, CR, and the maximum eigenvalue λ_{max} are computed. A CR value below the threshold of 0.1 is considered acceptable, the resulting KPI weights are deemed reliable.

Phase 3 – Prioritization of production processes using TOPSIS

In the final phase, the TOPSIS algorithm is applied to prioritize the manufacturing operations based on their potential for sustainability-oriented improvement. The process begins with the normalization of the decision matrix that incorporates the SMP data for each production process with respect to the predefined sustainability KPIs. To ensure comparability across criteria with different units and scales, each value in the matrix is normalized using vector normalization.

Subsequently, the normalized matrix is weighted using the criteria weights obtained from the AHP analysis. This results in a weighted and normalized decision matrix, which serves as the basis for identifying the ideal solution and anti-ideal solution. The ideal solution represents the best attainable performance, while the anti-ideal solution reflects the worst.

The Euclidean distances of each production process to the ideal and anti-ideal solution are calculated based on its performance across all sustainability KPIs. These distances are then used to determine the relative closeness coefficient C_i (TOPSIS score) of each alternative to the ideal solution, where higher values indicate better performance and closer proximity to the ideal solution.

After completing the computational steps, the algorithm generates output data that includes the calculated TOPSIS scores for each process and the AHP consistency ratio. As an extension to the computed TOPSIS scores, the key KPIs that predominantly influence the sustainability performance of processes requiring improvement are identified and presented, enabling targeted decision-making. These outputs are also returned in JSON format. Before the JSON output data is retrieved, the results undergo a final validation step to ensure structural correctness and completeness. Once validated, the output data is transmitted back to the SMP, where it becomes available for further processing.

By combining the structured and transparent weighting capabilities of AHP with the TOPSIS algorithm, the proposed framework enables a comprehensive, objective, and data-driven identification of sustainability potentials within values streams. The integration of real-time data ensures that decision-making is not only evidence-based but also dynamically adaptable to evolving operational contexts.

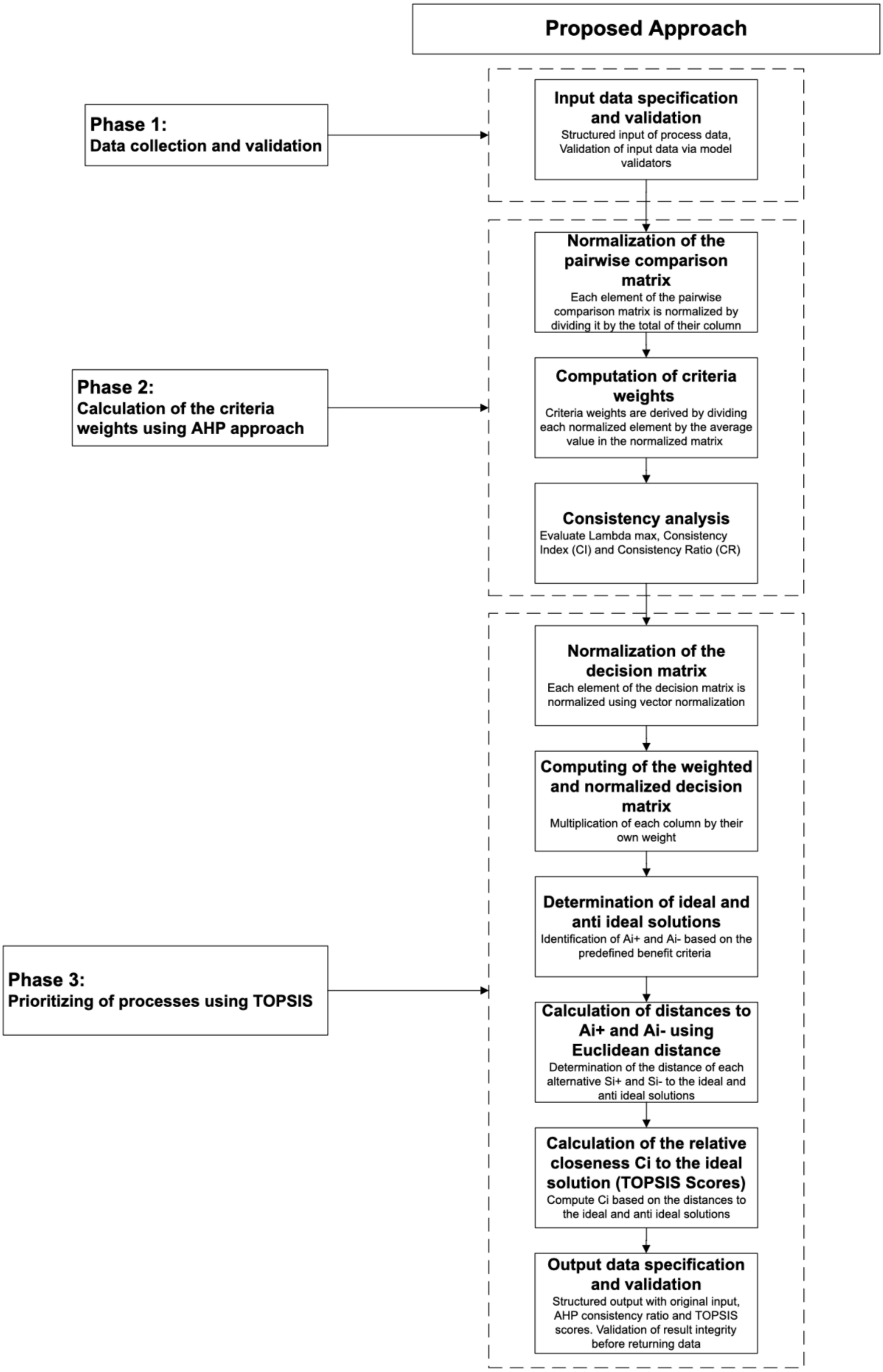

Figure 39: Proposed Approach – Combination of the AHP methodology and the TOPSIS algorithm

After presenting the overall workflow of SPDA, the following section provides a code-level analysis, offering a detailed examination of the underlying implementation.

5.3.2 Code-Level Analysis of SPDA using Python

This section examines the implementation of SPDA at the code level, detailing the key functions, logical structure, and Python libraries involved. The aim is to foster transparency and reproducibility while offering insights into the algorithmic structure.

Use of Python Libraries in Algorithm Implementation

The integration of libraries plays a crucial role in streamlining the programming workflow and enabling robust functionality. In this work, several Python libraries are employed to implement a web-based decision-support algorithm based on the combination of AHP method and TOPSIS algorithm. These libraries are imported at the beginning of the program to ensure consistent availability throughout the code execution. Figure 40 illustrates the technical implementation of these libraries.

```
from fastapi import FastAPI
from pydantic import BaseModel, model_validator
from typing import Self
from typing import Annotated
from typing import List
from typing import Union
from fractions import Fraction
import numpy as np
import math
```

Figure 40: Imported libraries

At the beginning of the code, essential libraries are imported to support both numerical computation and API functionality. The FastAPI framework is used to expose the algorithm as a web-based API, allowing users to interact with it through a user-friendly interface via Swagger UI. The BaseModel class from the pydantic library ensures strict data validation for the input parameters, which is critical for the reliability and integrity of the computations.

Numerical operations, especially matrix calculations required by the AHP method and TOPSIS algorithm, are performed using the numpy library. The math module is also imported to provide additional mathematical functions. The fractions module enables precise handling of ratio-based comparisons using rational numbers, enhancing the accuracy of the pairwise comparison matrices. The code further leverages modern

Python features such as type annotations (Annotated, List, Union) to ensure type safety and clarity of the data model.

Together, these libraries form the technical foundation of SPDA by enabling robust input validation, efficient numerical analysis, and seamless web-based access. This architecture ensures that the decision-making logic is both accessible to users and transparent in its execution.

Following the integration of the required libraries, the next step involves initializing the FastAPI application, which establishes a secure and structured interface for web-based data exchange.

Initialization of the FastAPI Application and Definition of the Input Data and Output Model

This initialization step is critical for enabling automated data exchange between SPDA and the "controller" component of SMP. The FastAPI application is instantiated with the statement app = FastAPI(title="SPDA API"), thus establishing the foundation for deploying the decision-support algorithm as a web-accessible API endpoint.

At the core of the application's data handling are two rigorously defined data models, implemented as subclasses of Pydantic's BaseModel, which ensure structured, consistent, and traceable communication between client and server. For a clear overview of the data structures and their relationships, Figure 41 visually depicts the input and output data models of SPDA, illustrating the flow and composition of information throughout the evaluation process.

The input data model "SPDAInput" precisely defines the structure and types of the expected input parameters required by SPDA. It consists of:

- kpi_count: An integer specifying the number of sustainability KPIs considered in the decision-making process.
- process_count: An integer denoting the number of production processes to be evaluated.
- pairwise_rankings: A two-dimensional list representing the pairwise comparison matrix used in the AHP method. This matrix contains either floats or strings convertible to rational numbers, reflecting the relative importance of each sustainability KPI compared to the others.
- kpi_values: A two-dimensional list containing the actual numerical sustainability KPI values associated with each process.
- benefit_criterias: A list of integers where each element is either 0 or 1, indicating for each sustainability KPI whether it has to be minimized (0) or maximized (1).
- path_factor: A list of integers representing the path factor for each process, which serves as a decision-support metric to facilitate the interpretation of

TOPSIS results and to highlight improvement potential in a structured and user-comprehensible manner.

This configuration block is a prerequisite for all following API operations, including data retrieval and ensures secure, structured, and consistent communication with the remote data source.

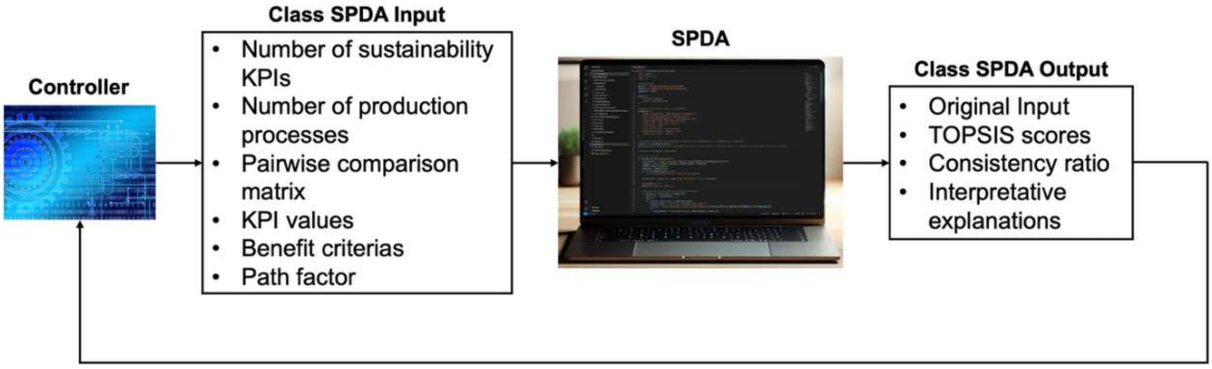

Figure 41: Input and Output of SPDA

The output data model "SPDAOutput" formally defines the structure and type constraints for the results returned by SPDA. It contains the following fields:

- input: An annotated instance of "SPDAInput", representing the exact input data used in the current evaluation run. This ensures full traceability and reproducibility of the results.
- scores: A list of floating-point numbers that represent the TOPSIS scores for each evaluated process.
- consistency_ratio: A single float value representing the consistency ratio derived from the AHP pairwise comparison matrix. It quantifies the logical coherence of the provided rankings and ensures that the weighting process was methodologically sound.
- explanations: A list of descriptive strings providing interpretative explanations on which KPIs significantly influence the sustainability performance of each process and indicating whether the process is on the main path or on a path that requires additional processing steps (rework, refinement etc.). These additional steps are represented by the Path Factor. This information is particularly relevant for processes identified as needing improvement, supporting targeted and evidence-based decision-making.

Together, these models provide a robust, well-structured framework for input validation and output representation, facilitating reliable downstream processing within SMP.

Building on this validated data structure, the next step involves the application of AHP to determine the relative importance of the sustainability KPIs.

Implementation of the AHP methodology

Figure 42 illustrates the application of the AHP method to derive relative weights for a set of sustainability KPIs and to perform a consistency analysis to ensure logical coherence in the pairwise comparisons.

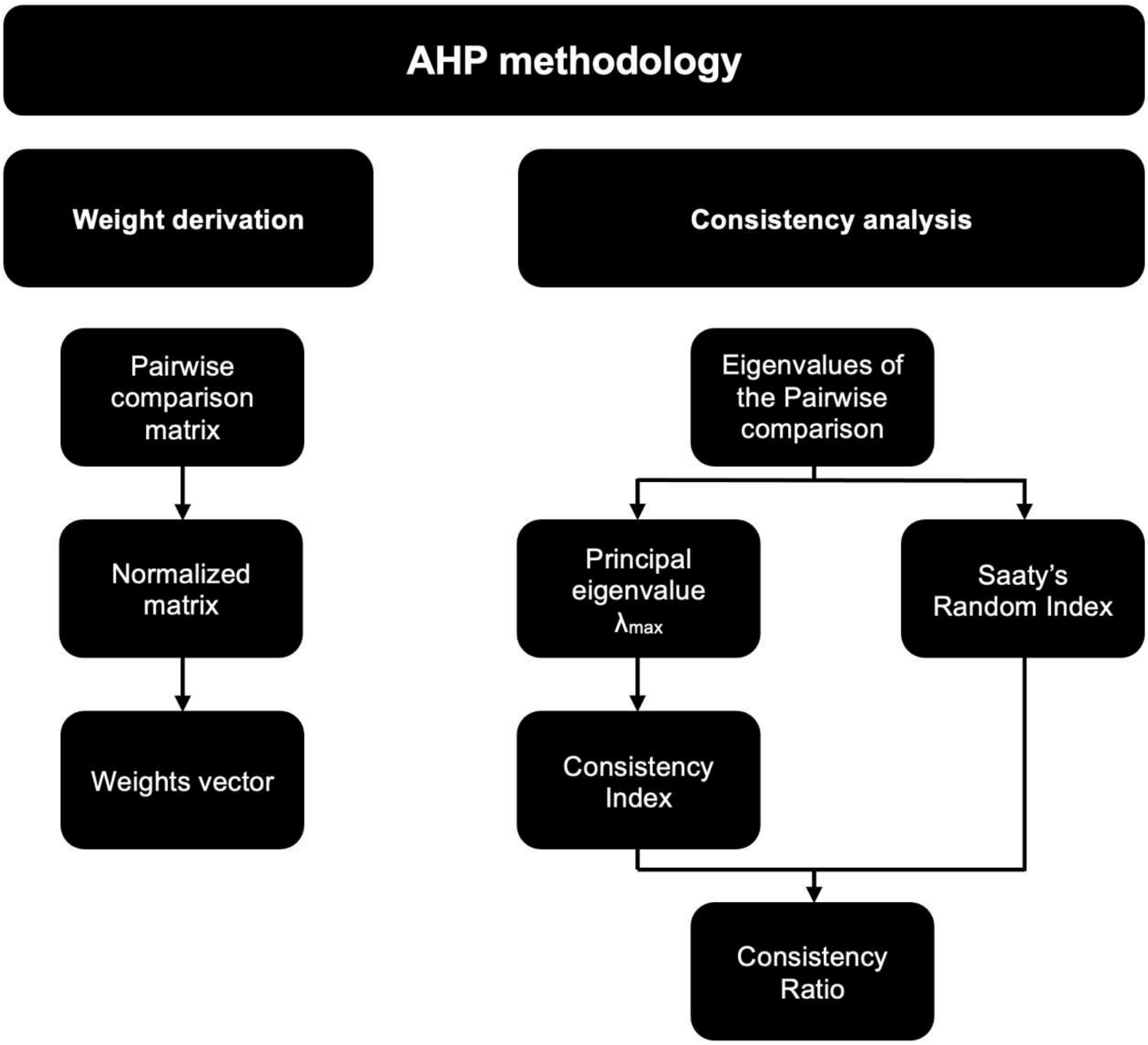

Figure 42: Application of the AHP methodology within the SPDA algorithm

The process of deriving weights starts by calculating the AHP weights from a pairwise comparison matrix, reflecting the relative importance of each sustainability KPI. When the pairwise comparison matrix may contain fractional strings (e.g. “1/3”), these are converted into floating-point values by parsing the input using Python’s Fraction class. The resulting numeric matrix is transformed into a structured format, and the values are normalized column-wise to ensure comparability. The weight for each sustainability KPI is subsequently calculated by averaging the elements of each row in the normalized matrix. This results in a vector representing the relative importance of each KPI, which serves as the output of the AHP method.

After the weight derivation, a consistency check is performed on the comparison matrix in order to ensure the reliability of the user's pairwise comparisons, as illustrated in Figure 42. This process involves calculating the eigenvalues λ of the pairwise comparison matrix, which reflects the degree of consistency in the judgments. The Consistency Index (CI) is derived from the principal eigenvalue λ_{max} and measures the deviation from perfect consistency. Using the CI together with predefined Random Index (RI) values proposed by Saaty, the Consistency Ratio (CR) is calculated. The CR quantifies the overall consistency of the comparisons, providing an objective metric to determine whether the judgments are logically coherent or require revision. If CR < 0.1, the level of consistency is considered acceptable, and the decision process is deemed reliable. Otherwise, inconsistencies are present, and it is recommended to review and revise the pairwise comparisons.

Following the determination of criteria weights using AHP, the TOPSIS method is applied to rank the production processes based on their sustainability performance.

Implementation of the TOPSIS algorithm for Multi-Criteria Decision Making and KPI Influence Analysis

Figure 43 illustrates the TOPSIS procedure and the subsequent KPI influence analysis within SPDA. First, the decision matrix is normalized using vector normalization based on the Euclidean norm, with special handling of zero-norm columns to prevent division by zero errors. Subsequently, the normalized matrix is weighted by multiplying each sustainability KPI by its associated weight, yielding the weighted decision matrix. This matrix serves as the foundation for determining the ideal and anti-ideal solutions. The ideal and anti-ideal solutions are derived by selecting either the maximum or minimum value for each sustainability KPI, depending on the corresponding entry in the benefit criterias list. Once the ideal and anti-ideal solutions are determined, the Euclidean distance of each production process from both solutions are calculated. These distances indicate how close a process is to the best or worst possible performance across all sustainability KPIs. The final TOPSIS score for each process is computed as the ratio of its distance to the anti-ideal solution to the sum of its distances from both the ideal and anti-ideal solutions. A lower TOPSIS score indicates a greater potential for improvement with respect to sustainability KPIs. In contrast, a higher TOPSIS score signifies that the process is nearer to the ideal solution, demonstrating stronger performance regarding sustainability KPIs.

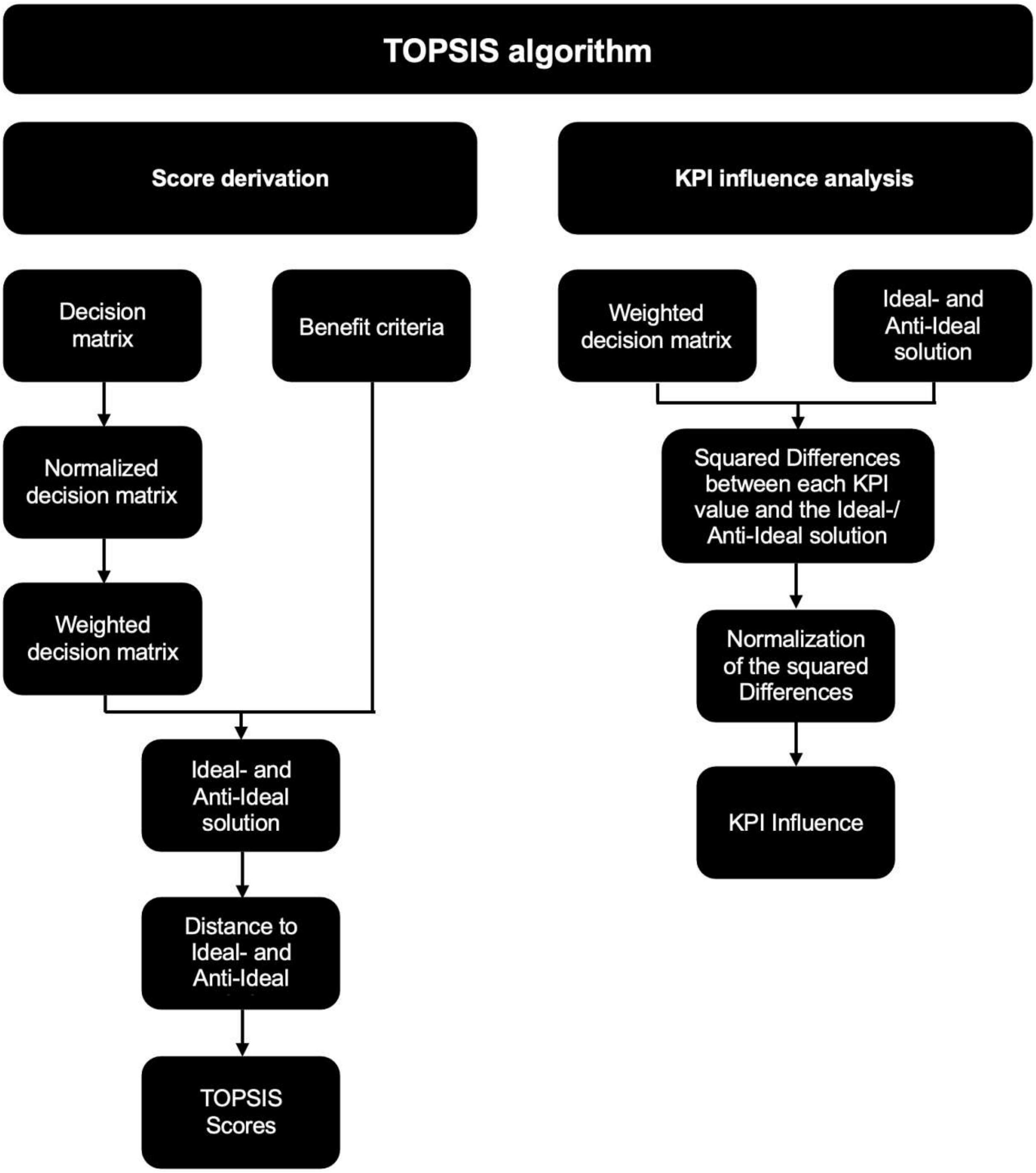

Figure 43: Implementation of the TOPSIS algorithm within SPDA

As illustrated in Figure 43, the analysis evaluates the contribution of each sustainability KPI to the distance of each process from the ideal and anti-ideal solutions within the TOPSIS framework. The underlying data comprise the weighted KPI values for each process, as well as the ideal and anti-ideal reference points. For each process, the squared deviations between the weighted KPI values and the corresponding values in the ideal and anti-ideal solutions are calculated. These differences are subsequently normalized to express the relative influence of each KPI on the process's distance to the ideal and anti-ideal solution. The output consists of two sets of values per process, each representing the KPI-specific contribution to the distance from one of the reference points, namely the ideal and the anti-ideal solution.

After the calculation of the TOPSIS scores and the corresponding KPI influence values, a qualitative interpretation is performed to support decision-making. This interpretation step uses the TOPSIS score of each process and the relative influence of each sustainability KPI on the process's distance from the ideal solution.

If the TOPSIS score is 0.50 or lower, the process is considered to have low conformity with the ideal solution. In such cases, KPIs with a high influence (influence value ≥ 0.25) are identified as potential contributors to the weak performance. These KPIs are explicitly mentioned in the interpretation to indicate where targeted improvements may be most effective.

If the TOPSIS score is between 0.51 and 0.75, the process s interpreted as having moderate conformity. The KPIs with the greatest influence are again reported, indicating possible levers for optimization.

When the TOPSIS score exceeds 0.76, no interpretation is generated, as the process is already performing well in terms of sustainability and shows little immediate potential for improvement.

If no KPIs significantly influence the process's distance (influence value ≤ 0.25), the explanation notes that no single KPI has a significant impact. By translating numerical results into descriptive statements, this step enables a clearer understanding of the evaluation outcomes and helps decision-makers identify meaningful starting points for process improvement.

Once the AHP and TOPSIS methods have been applied to generate weighted rankings of production processes, SPDA performs a series of validation steps to safeguard the accuracy of inputs and the robustness of analytical outcomes.

Validation Procedures within SPDA

Within SPDA, several validation steps have been implemented to identify and manage issues such as incomplete data, inconsistent input values, or structural irregularities before the core analytical computations are performed. By verifying the accuracy and integrity of the input data and intermediate results, the algorithm minimizes the risk of errors and improves the consistency of its outputs. This contributes to the reliability and general applicability of the algorithm across different use cases involving sustainability assessment and multi-criteria decision-making.

The validation process begins with a thorough examination of the input parameters. This validation is implemented using a model_validator method within a Pydantic model, which is executed automatically after the input data has been parsed. As a first step, as illustrated in Figure 44, the pairwise comparison matrix is validated. The routine checks whether the matrix has the correct square shape, specifically with dimensions kpi_count x kpi_count. This structural requirement ensures that each sustainability KPI can be consistently and systematically compared to every other KPI.

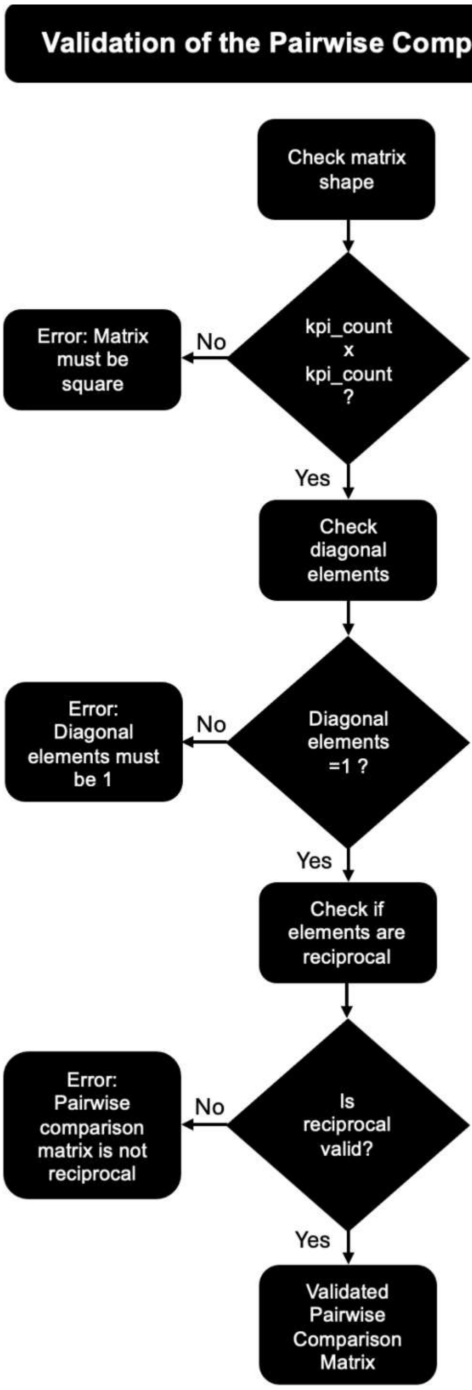

Figure 44: Validation of the Pairwise Comparison Matrix

Furthermore, the matrix is subjected to a reciprocity check, a core requirement of the AHP methodology. According to this principle, for any two criteria i and j, the element at position (i, j) must be the mathematical reciprocal of the element at position (j, i), that is, $a_{ij} = 1 / a_{ji}$.

Additionally, all diagonal elements (i, i) must be equal to 1, reflecting that each criterion is equally important when compared to itself. To ensure numerical precision and robustness, the validation also accommodates fractional string representations by converting them to rational numbers using Python's Fraction class.

This rigorous validation safeguards against inconsistent or malformed input, which could otherwise distort the outcome of the AHP weighting process and compromise the decision-making reliability of SPDA.

Another validation step is applied to the decision matrix used in the TOPSIS algorithm, as shown in Figure 45. This step ensures the structural consistency of the decision matrix, which contains the sustainability KPI values for each process. Specifically, the number of rows must match the number of processes (process_count), and the number of columns must equal the number of sustainability KPIs (kpi_count). Any deviation from this expected structure would compromise the validity of subsequent computations and may result in incorrect or misleading outcomes. By enforcing this structural requirement, the algorithm enhances both reliability and robustness of the decision-making process.

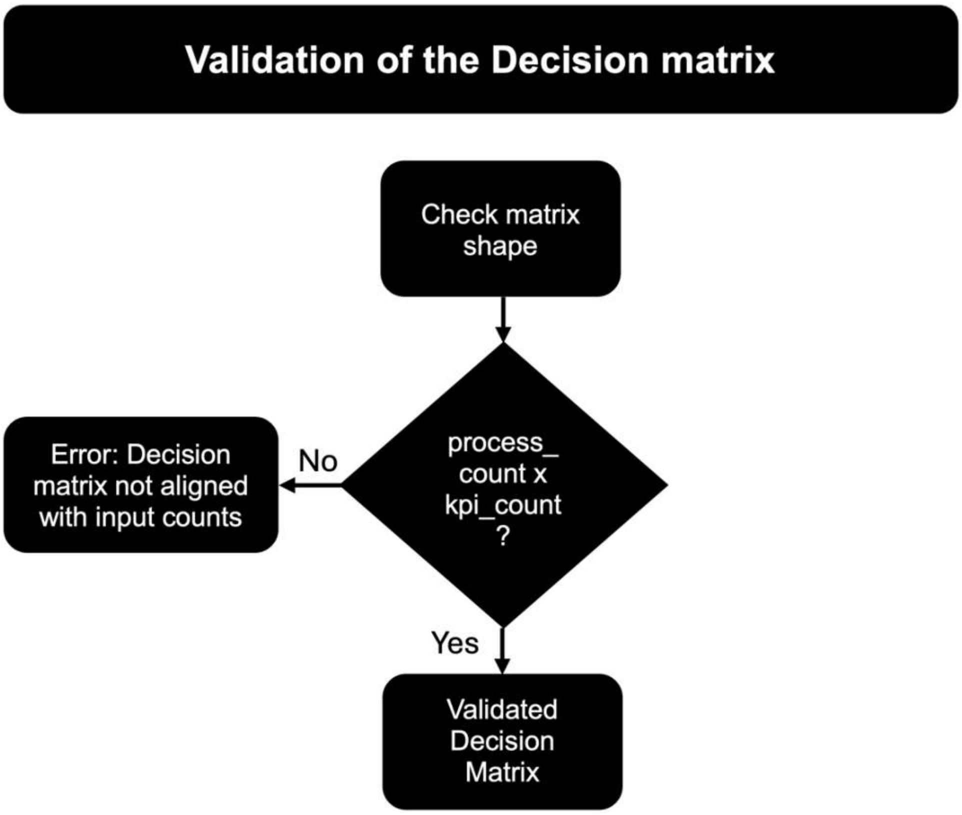

Figure 45: Validation of the Decision Matrix

Further validation is required for the benefit criteria list, which plays a fundamental role in the execution of the TOPSIS algorithm, as illustrated in Figure 46. Firstly, it verifies that the length of the benefit_criterias list corresponds exactly to the number of sustainability KPIs, as defined by the variable kpi_count. This requirement ensures that each criterion is explicitly associated with a corresponding benefit directive.

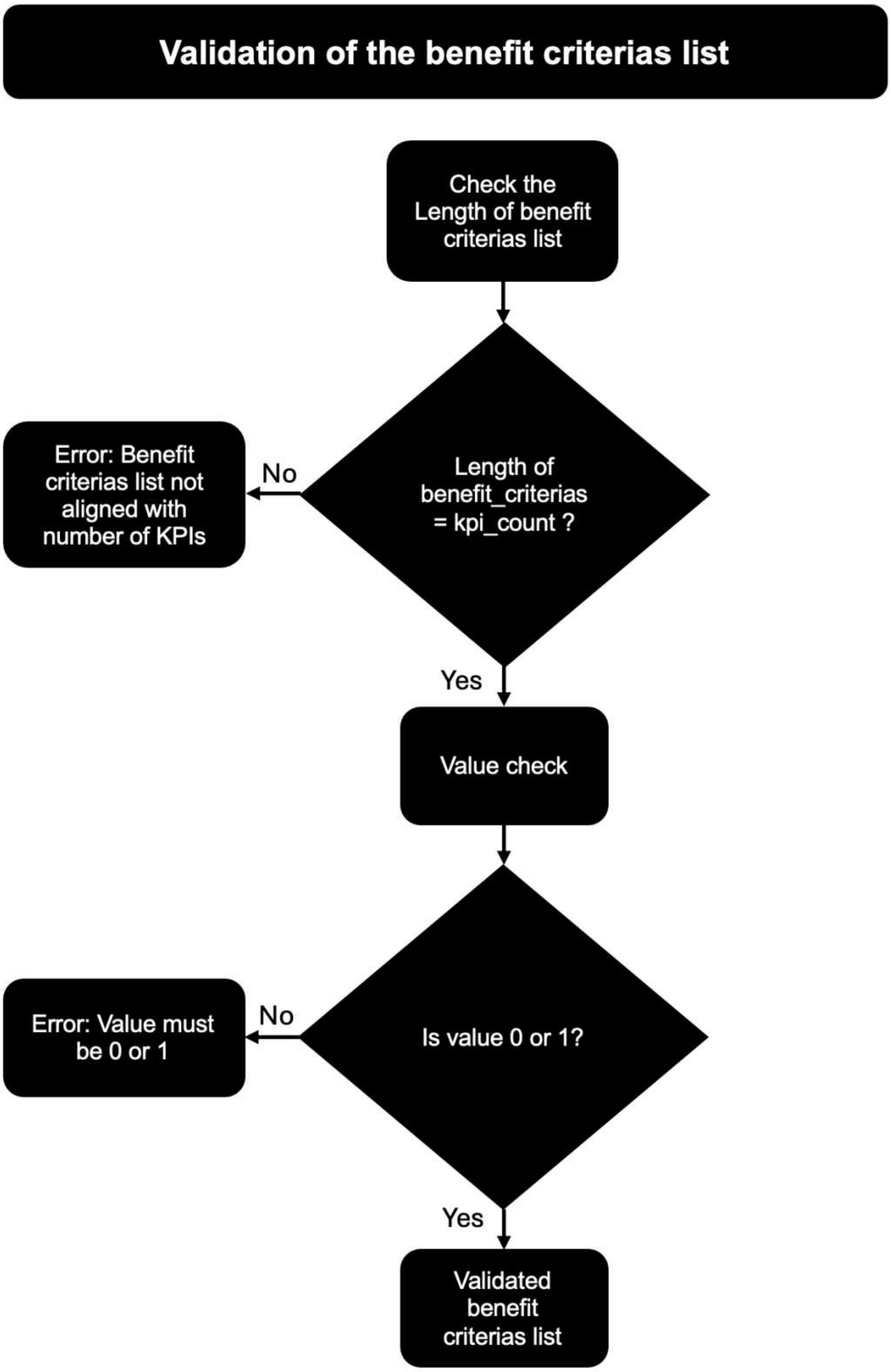

Figure 46: Validation of the benefit criterias list

Secondly, the validator enforces strict admissibility of values within the benefit_criterias list. Each element must be either 0 or 1, where 0 denotes a criterion to be minimized and 1 denotes a criterion to be maximized. These binary indicators are indispensable for correctly identifying the ideal and anti-ideal solutions, which underpin the TOPSIS ranking procedure. Any deviation from these constraints results in a validation error, thereby preventing incorrect data from being used and ensuring the decision-making process remains reliable.

An additional validation step is applied to the Path Factor input, which is used to support the interpretation of the TOPSIS results. This step ensures that the length of the path_factor list matches exactly the number of processes (process_count), as illustrated in Figure 47. Any discrepancy would indicate a mismatch between process-specific data and the Path Factor information, potentially undermining the interpretative explanations and the reliability of the decision-support output. By enforcing this consistency, the algorithm guarantees that each process is properly associated with its corresponding Path Factor, thereby enhancing the accuracy and interpretability of the results.

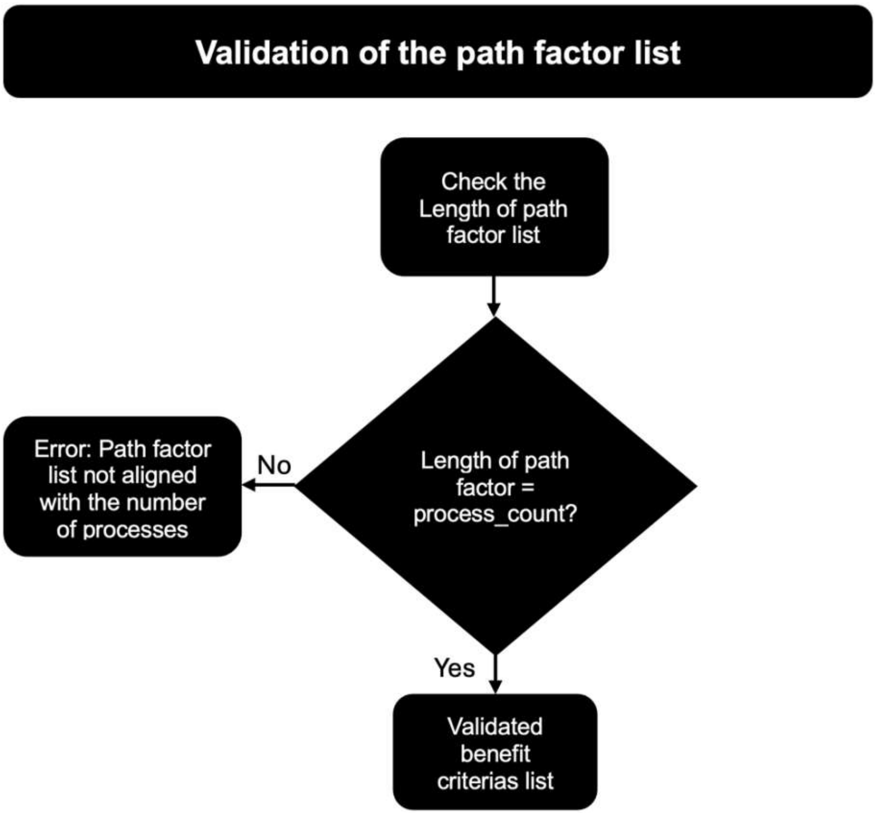

Figure 47: Validation of the path factor list

After the input data has been successfully validated, an additional verification step is applied to the output data. This validation ensures structural consistency between the computed TOPSIS scores and the defined process configuration, as illustrated in Figure 48. Specifically, it checks whether the number of generated scores matches the number of production processes specified in the input via the process count. This alignment is critical to ensure that each evaluated process is accurately represented by a single corresponding score, thereby preserving the interpretability and correctness of the final ranking.

Any discrepancy between the number of scores and the declared number of processes would indicate a structural inconsistency within the evaluation pipeline. If such a mismatch occurs, the validation mechanism raises an error, halting further processing to prevent the propagation of incorrect or misleading results.

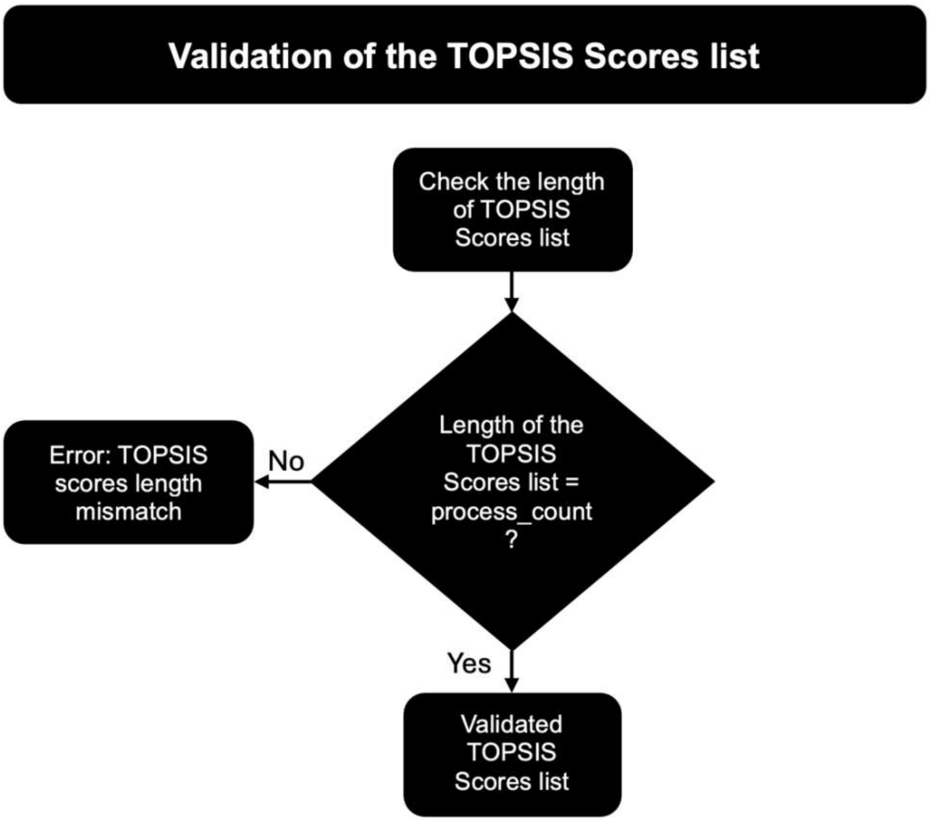

Figure 48: Validation of the TOPSIS Scores list

By enforcing this constraint, the validation contributes significantly to the robustness, transparency, and reliability of SPDA, ensuring that its outputs remain trustworthy and analytically sound.

As a final step, all previously validated inputs and algorithmic components are brought together within an integrated execution flow. This step ensures that the weight calculation, consistency assessment, process evaluation, and explanation generation are carried out in the correct sequence and with verified data. By consolidating these operations into a single coherent process, the algorithm delivers a complete and reliable decision output. This structured orchestration enables automated, transparent, and robust evaluation of production processes, making the results directly accessible for decision-making purposes.

Having detailed SPDA, the following chapter evaluates its performance by applying it to a practical case study.

6 Evaluation / Results

To evaluate SPDA, the proposed approach is applied to a case study conducted in a refrigerator and freezer manufacturing facility described by (Khakpour et al., 2023). The factory produces a variety of white goods, including different models of refrigerators and freezers. For this study, a specific refrigerator-freezer model is selected. The following sections provide a detailed description of the value stream, followed by the application of SPDA to the case study and a critical discussion of the results.

6.1 Value Stream of the refrigerator-freezer

The selected refrigerator-freezer model is produced through a sequence of discrete manufacturing processes, including Sheet Extruding, Liner Forming, Cabinet Assembling, Cabinet Metal Forming, Cabinet Foaming, Refrigerant Cycle Assembling, Panel Forming, Pressing, Door Assembly, Door Foaming and Final Assembling (Khakpour et al., 2023). The corresponding value stream map is illustrated in Figure 49. The manufacturing process is divided into two primary streams. The upper stream represents the cabinet manufacturing process, while the lower stream corresponds to door production. These two streams are subsequently integrated during the final assembly process, where the complete refrigerator-freezer unit is assembled. Since the cabinet manufacturing process constitutes the critical stream within the value stream, this process is used as the basis for evaluating the system.

Sustainability KPIs employed in this analysis are adopted from the case study by (Khakpour et al., 2023), which delineates a robust set of quantitatively defined KPIs specifically tailored to the cabinet manufacturing process. These KPIs encompass various dimensions.

Owing to the specificity and completeness of the sustainability metrics provided for the cabinet manufacturing stream, the inclusion of the Path Factor, typically utilized to account for secondary or auxiliary process streams, was considered methodologically unnecessary for the present evaluation. Consequently, the Path Factor was excluded, ensuring analytical focus and interpretative clarity within the critical stream under investigation.

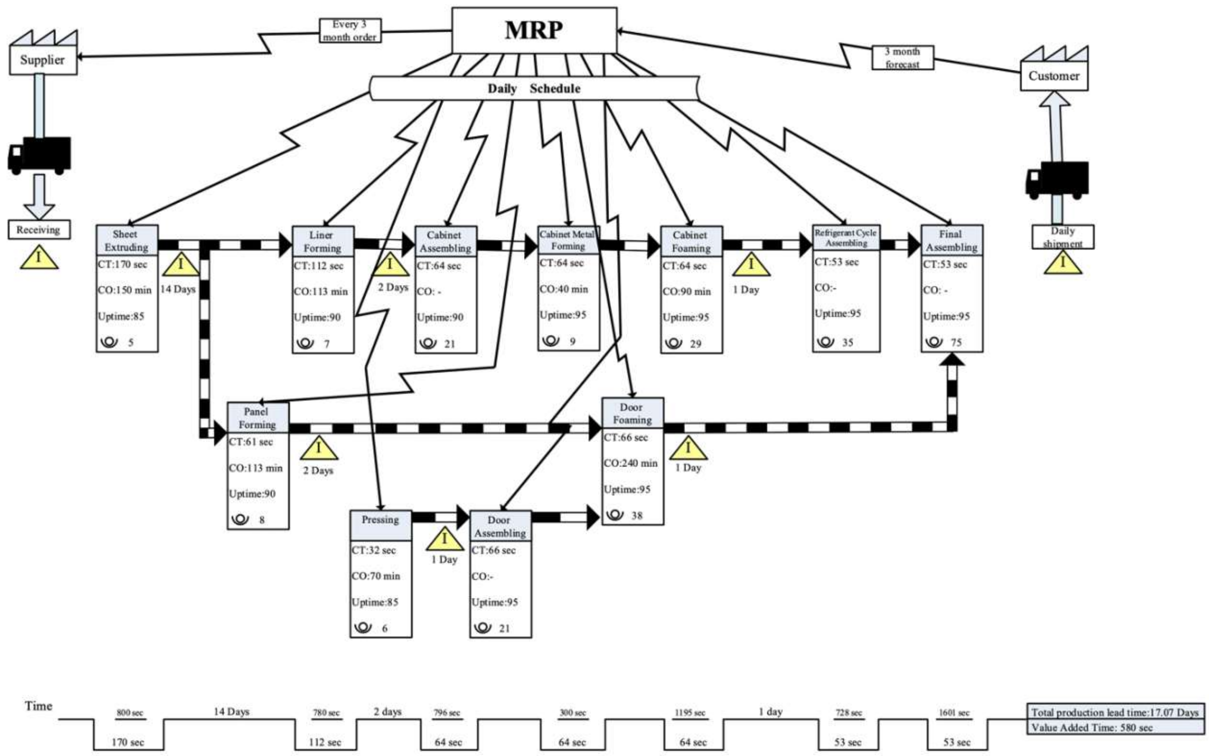

Figure 49: Value Stream map of the refrigerator-freezer (Khakpour et al., 2023)

For each process within the cabinet manufacturing stream, input data were collected, encompassing the three pillars of sustainability, as detailed in Table 3.

Sustainability Pillar	Sustainability KPI	Unit
Economic	Lead time (LT)	sec
	Process costs (PC)	monetary units
	Inventory time (IT)	sec
Environmental	Material consumption (MC)	kg
	Energy consumption (EC)	kWh
	Waste of energy consumption (WoEC)	kWh
Social	Noise level (NL)	dB(A)
	Accident rate (AR)	%
	Skilled manpower (SM)	%

Table 3: Selected sustainability KPIs

Furthermore, material consumption specifically refers to the consumption of petroleum-based materials (in kg), including Acrylonitrile Butadiene Styrene (ABS), Methylene Diphenyl Diisocyanate (MDI) and Polyol (P). Process costs comprise petroleum-based material costs, manpower costs, facilities and equipment depreciation costs, energy consumption costs, and operational costs.

The sustainability KPI values for each discrete manufacturing process within the cabinet manufacturing stream are summarized in the Table 4. This compilation provides a comprehensive overview of the input data utilized for the evaluation of SPDA.

Process	LT	PC	IT	MC	EC	WoEC	NL	AR	SM
Sheet Extruding	800	41.725	0	20.55	32.48	2.63	84	2	90
Liner Forming	780	8.107	14	0	20.25	3.54	85	0	87
Cabinet Assembling	796	3.588	2	0	1.95	0	77	2	78
Cabinet Metal Forming	300	5.08	0	0	2.5	0	77	2	79
Cabinet Foaming	1195	55.04	0	13.6	14	0.15	82	0	87
Refrigerant Cycle Assembling	728	2.393	1	0	0.6	0	72	0,5	84
Final Assembling	1601	5.14	0	0	1.03	0	72	0	91

Table 4: Sustainability KPIs per process in cabinet manufacturing

6.2 Assumptions and Scenario-Based Evaluation of SPDA

The case study presented by (Khakpour et al., 2023) provides comprehensive sustainability-related performance data for each process step within the cabinet manufacturing stream. However, the original study does not include an evaluation or weighting of the relative importance of the sustainability KPIs. As SPDA requires a pairwise comparison matrix to determine the weights of the sustainability KPIs, assumptions were made to facilitate the evaluation process.

To ensure a structured and meaningful evaluation of the algorithm, three different weighting scenarios (S1, S2, S3) were defined, each placing the primary focus on one of the three sustainability dimensions. For each scenario, the respective criteria were prioritized in the pairwise comparison matrix to reflect a dominant sustainability perspective. This approach allows for the assessment of the algorithm's responsiveness and plausibility under varying strategic priorities.

To ensure consistency in the evaluation, each sustainability KPI was assigned a corresponding benefit criterion based on its intended improvement direction. As shown in Table 5, most KPIs are to be minimized, while the proportion of skilled manpower is to be maximized. These benefit criteria were consistently applied across all scenarios.

Sustainability Pillar	Sustainability KPI	Benefit Criteria
Economic	Lead time (LT)	Minimize
	Process costs (PC)	Minimize
	Inventory time (IT)	Minimize
Environmental	Material consumption (MC)	Minimize
	Energy consumption (EC)	Minimize
	Waste of energy consumption (WoEC)	Minimize
Social	Noise level (NL)	Minimize
	Accident rate (AR)	Minimize
	Skilled manpower (SM)	Maximize

Table 5: Benefit criteria assigned to the sustainability KPIs in the evaluation process

The following section presents and analyzes the results obtained by applying SPDA under the three assumed weighting schemes. To facilitate the interpretation of the

TOPSIS scores for each process across all three weighting scenarios, a traffic light system was implemented. This visual classification supports the identification of processes with the highest improvement potential based on their relative alignment with the sustainability configuration. Specifically, scores between 0.00 and 0.50 are marked in red, indicating low conformity with the ideal solution and thus a high need for improvement. Scores from 0.51 to 0.75 are colored orange, representing moderate conformity, where some improvements may still be necessary. Finally, scores in the range of 0.76 to 1.00 are shown in green, signaling strong conformity with the ideal solution and indicating processes with relatively good sustainability performance. This traffic light system enables a clear and intuitive assessment of the results and supports decision-makers in identifying critical areas for sustainability improvement.

Weighting Scenario 1: Focus on economic KPIs

In the first evaluation scenario, the pairwise comparison matrix was constructed to emphasize economic sustainability KPIs. This scenario simulates a decision-making context in which economic performance is the primary concern. Based on the pairwise comparison matrix, the relative weights of all nine sustainability KPIs were derived using AHP. The resulting weights are visualized in a horizontal bar chart, as illustrated in Figure 50.

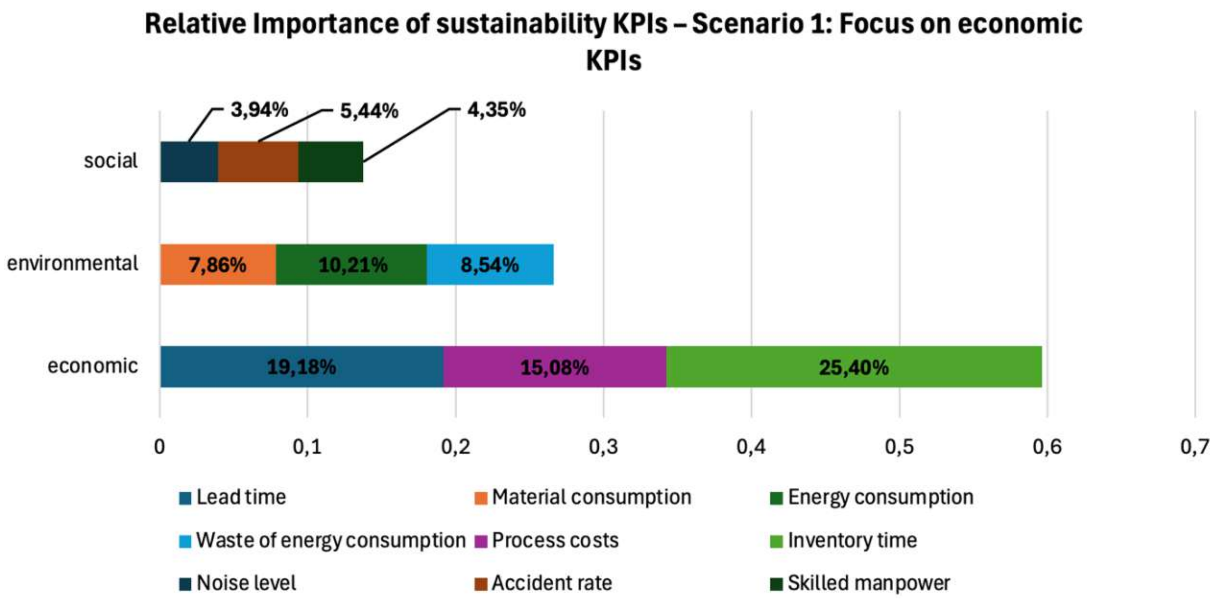

Figure 50: AHP-derived weights of sustainability KPIs – Scenario 1: Focus on economic KPIs

As expected, the most influential criteria in this scenario are inventory time, lead time, and process costs, which together account for 59.66% of the total weight. These indicators are all associated with the economic performance of the manufacturing system. In contrast, environmental (26.61%) and social (13.73%) KPIs receive lower weights, reflecting their subordinate priority within this weighting scenario. Consequently, the final process ranking is primarily driven by the performance of each process with respect to the economic indicators.

The TOPSIS scores and corresponding process ranking are shown in Figure 51. The highest-ranking processes in this scenario are Cabinet Metal Forming (0.91) and Refrigerant Cycle Assembling (0.89). Both processes exhibit low lead times (300 sec and 728 sec, respectively), minimal or no inventory times, and low process costs (5.08 and 2.39 monetary units). These favorable values in the most heavily weighted economic KPIs result in high TOPSIS scores, positioning them close to the ideal solution under the given weighting scheme.

In contrast, Liner Forming receives the lowest TOPSIS score (0.36), primarily due to a combination of moderately high lead time (780 sec) and noticeable inventory time (14 days). Similarly, Sheet Extruding (score: 0.61) shows a very high process cost (41.73 monetary units) and moderately high lead time (800 sec), which significantly reduce its performance score despite favorable values in other dimensions.

Cabinet Foaming receives intermediate scores (0.64). Although Cabinet Foaming has the highest lead time (1195 sec) and highest process cost (55.04 monetary units) among all processes, it performs moderately well in environmental and social KPIs. However, due to the lower weights of these dimensions in this scenario, these strengths only partially offset its economic disadvantages.

Interestingly, Final Assembly and Cabinet Assembling achieve comparatively high TOPSIS scores (0.76 and 0.82, respectively), despite their high or moderate lead times (1,601 seconds and 796 seconds). This favorable outcome can be attributed to their low process costs (5.414 and 3.59 monetary units) and no or low inventory times (0 days and 2 days), which are closely aligned with the dominant economic criteria in this scenario. These advantageous values in the most heavily weighted KPIs offset the longer lead times and contribute significantly to the overall sustainability performance of the processes.

The ranking of the processes clearly reflects the relative weighting derived from the pairwise comparison matrix. The AHP-derived weights emphasize economic performance, and the TOPSIS method integrates these preferences into a composite score for each process. This alignment between input data and results confirms the consistency of the algorithm and suggests that the outcomes are plausible and reliable.

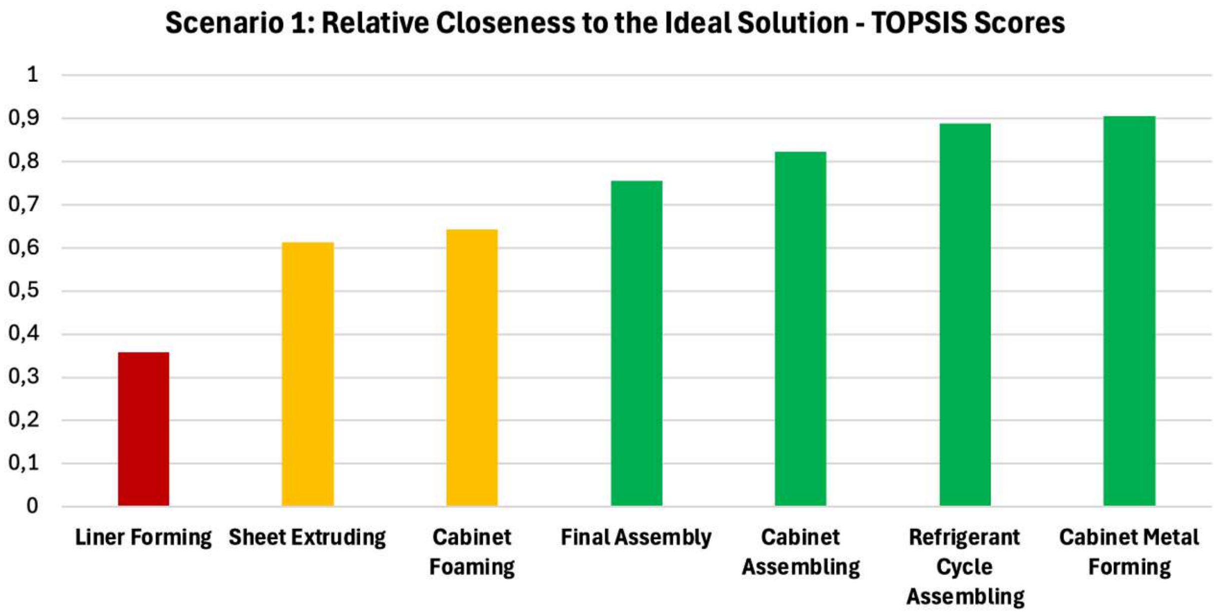

Figure 51: Scenario 1 – TOPSIS scores

Weighting Scenario 2: Focus on environmental KPIs

In the second evaluation scenario, the pairwise comparison matrix was constructed to focus on environmental sustainability KPIs. This scenario reflects a decision-making context in which ecological performance is prioritized over economic and social considerations. The AHP-derived weights for all nine sustainability KPIs are shown in Figure 52 as a horizontal bar chart.

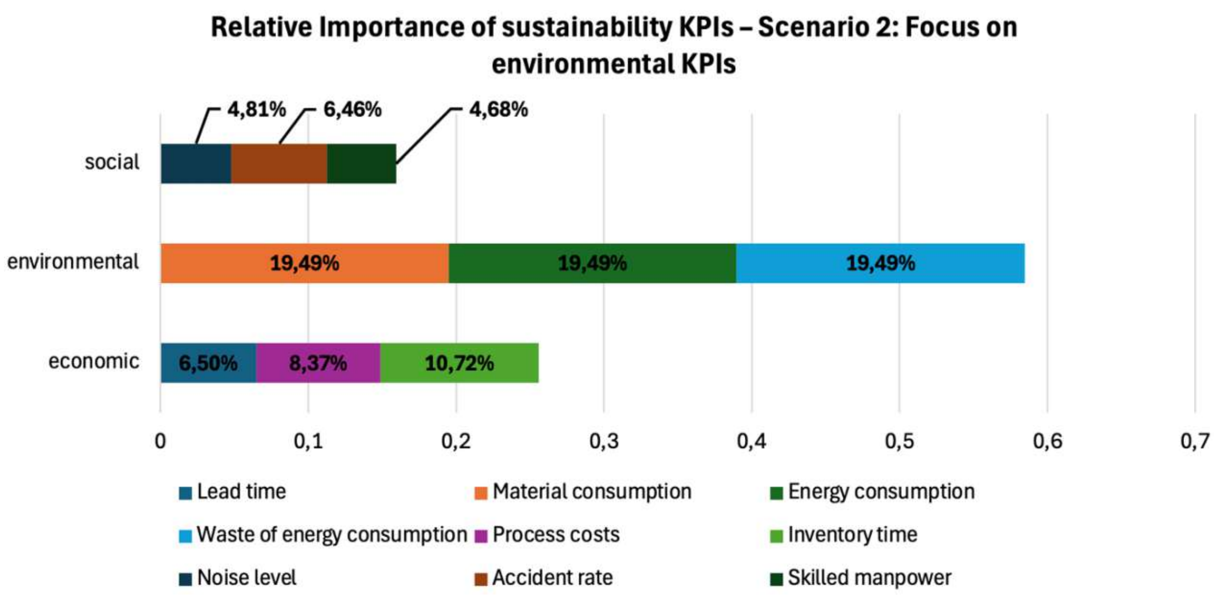

Figure 52: AHP-derived weights of sustainability KPIs – Scenario 2: Focus on environmental KPIs

Accordingly, the AHP-derived weights place the greatest emphasis on material consumption, energy consumption, and waste of energy consumption, each contributing approximately 19.5% to the total. Combined, these environmental indicators account for over half of the total weighting (58.47%), clearly dominating the evaluation. Economic criteria (25.59%) and social indicators (15.95%) play a subordinate role in this scenario. As visualized in Figure 52, this distribution shifts the focus of the analysis towards ecological performance, ensuring that the subsequent ranking of manufacturing processes is primarily influenced by their environmental impact.

The TOPSIS scores for Scenario 2 are illustrated in Figure 53. The highest-ranking process is Refrigerant Cycle Assembling (0.95), followed closely by Cabinet Metal Forming (0.89) and Final Assembling (0.89). These processes achieve strong scores primarily due to minimal or zero material and energy consumption as well as zero waste of energy, which are the criteria that dominate the weighting in this scenario. For example, Refrigerant Cycle Assembling records only 0.6 kWh of energy consumption and exhibits zero material consumption and energy waste, which aligns closely with the prioritized environmental KPIs.

Despite favorable performance in selected social indicators, Sheet Extruding (0.32) and Liner Forming (0.47) receive the lowest scores due to their relatively high energy consumption. For example, Sheet Extruding requires 20.55 kg of petroleum-based material and 32.48 kWh of energy, which substantially reduces its score within the environmentally weighted scenario, where social KPIs have comparatively less impact.

Cabinet Assembling (0.87) attains a high TOPSIS score, primarily due to its low energy consumption combined with zero material consumption and the absence of energy waste. These attributes lead to higher scores due to the environmentally focused weighting applied in this scenario. In contrast, Cabinet Foaming (0.60) receives only a moderate score, as its substantial energy and material consumption detracts from its performance under the environmentally focused weighting scheme.

The results demonstrate consistent and plausible outcomes, confirming the algorithm’s correctness and its robustness in evaluating processes under environmental priorities.

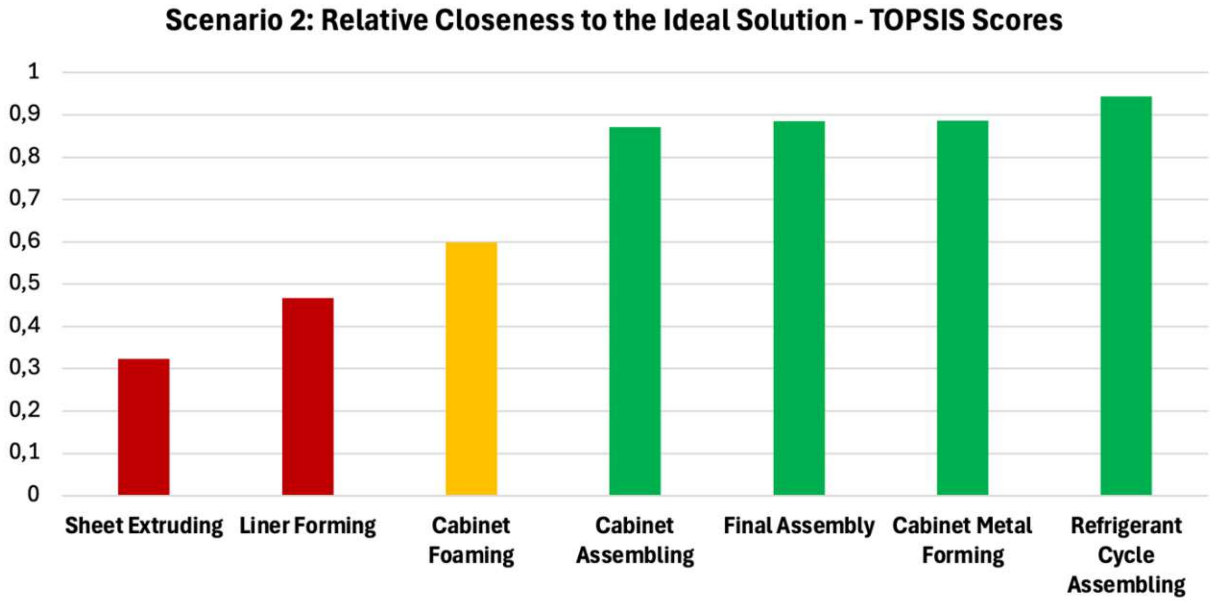

Figure 53: Scenario 2 – TOPSIS scores

Weighting Scenario 3: Focus on social KPIs

In the third evaluation scenario, the pairwise comparison matrix was structured to prioritize social sustainability KPIs, representing a decision-making context where social factors are given precedence over economic and environmental concerns. The resulting weights are visualized in a horizontal bar chart, as depicted in Figure 54.

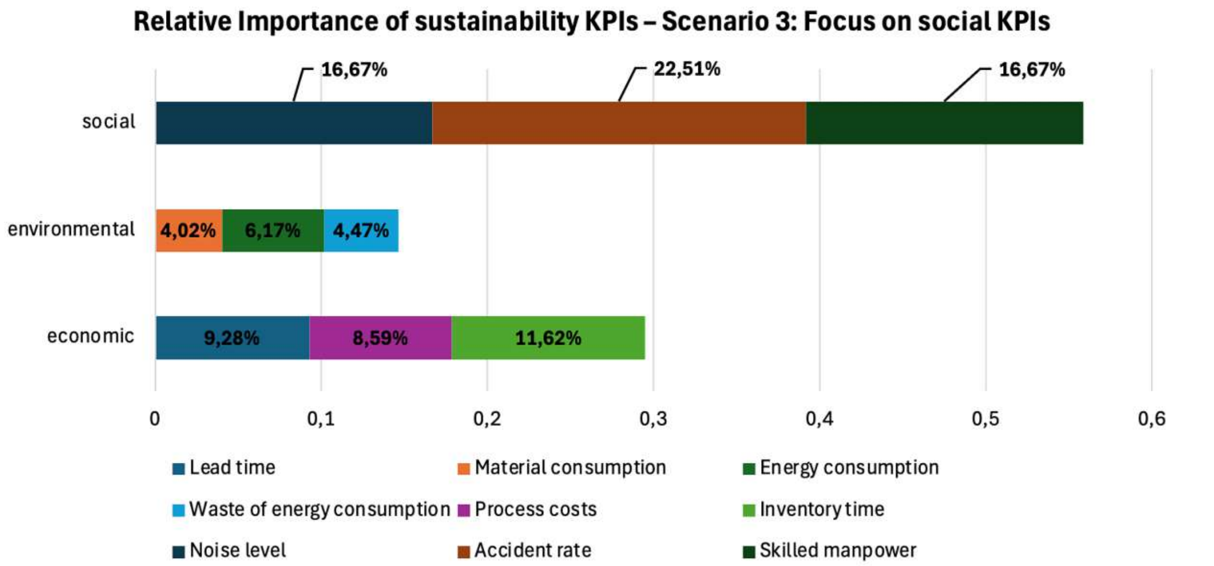

Figure 54: AHP-derived weights of sustainability KPIs – Scenario 3: Focus on social KPIs

The weights assign the highest importance to social indicators, notably accident rate, noise level, and skilled manpower, which collectively account for 55,85% of the total weighting. Economic KPIs represent around 29.49%, while environmental criteria contribute a smaller share of roughly 14.66%. This weighting scheme clearly shifts the evaluation emphasis towards social performance, ensuring that the ranking of manufacturing processes is primarily driven by their social impact.

Figure 55 visualizes the TOPSIS scores and the resulting ranking of the evaluated processes. In this scenario, Refrigerant Cycle Assembling (0.82) and Final Assembling (0.82) achieve the highest scores. Both processes demonstrate strong performance in socially relevant criteria, such as the lowest noise level (72 dB(A)) among all processes, as well as low accident rates (0 and 0.5 %, respectively).

Cabinet Foaming ranks in the mid-range with a score of 0.71. While it exhibits high lead time and process costs, it benefits from favorable social indicators, most notably a zero accident rate and a high proportion of skilled labor (87%), which significantly contribute to its score in this socially focused assessment.

Similarly to Cabinet Foaming, Liner Forming benefits from strong social performance indicators. An excellent accident rate of 0% and a relatively high proportion of skilled labor (87%) support its ranking. However, these strengths are partially counterbalanced by a long inventory time of 14 days, which negatively impacts its TOPSIS score. As a result, the process achieves a moderate performance level with a score of 0.57.

Cabinet Metal Forming (0.51) and Cabinet Assembling (0.48) achieve lower scores due to relatively high accident rates (2%) and lower proportions of skilled labor (79% and 78%). These factors reduce their evaluation in the socially weighted scenario, despite strengths in other sustainability dimensions. Sheet Extruding ranks lowest (0.41), primarily due to a combination of a high accident rate (2%) and relatively high noise levels (84 dB(A)). These factors place this process at the bottom of the ranking.

Overall, the results of scenario 3 provide strong evidence of the algorithm's accuracy and robustness.

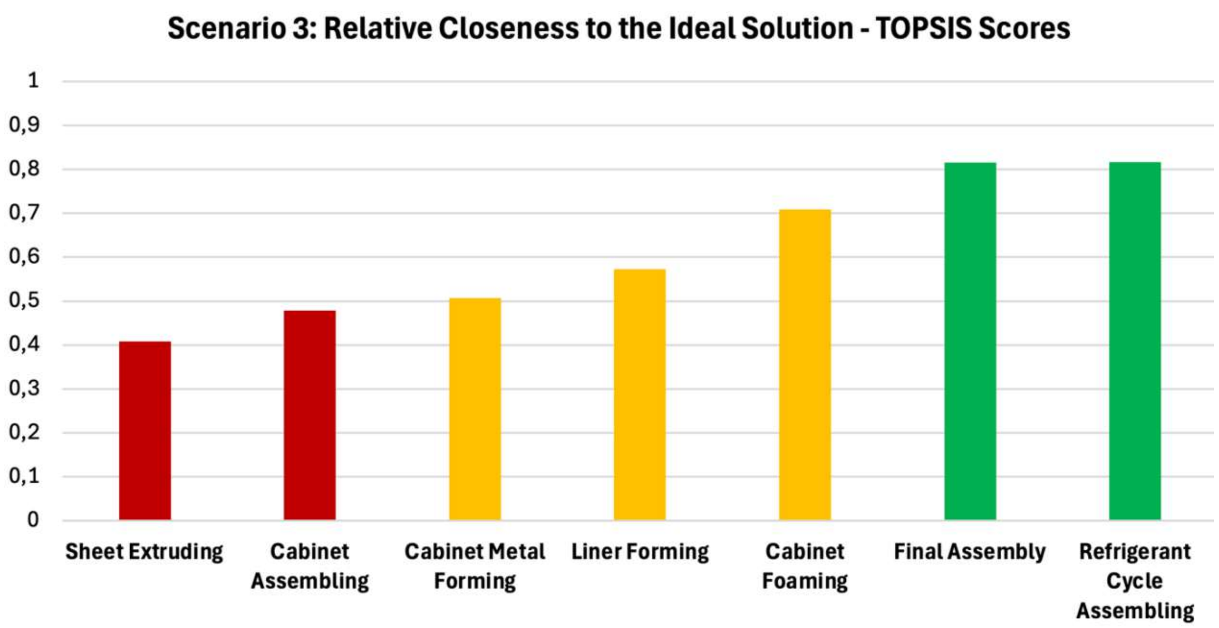

Figure 55: Scenario 3 – TOPSIS scores

6.3 Results

To evaluate the performance and applicability of SPDA, three distinct scenarios were tested using a case study from the manufacturing sector. Each scenario reflects different prioritizations of sustainability criteria, allowing for a comprehensive assessment of the algorithm's adaptability and decision logic. The resulting process rankings are analyzed in terms of consistency with the input preferences and the resulting trade-offs between economic, environmental, and social KPIs. To facilitate comparison and highlight performance patterns across all scenarios, Table 6 visualizes a heatmap displaying the TOPSIS scores of the seven evaluated processes across the three sustainability scenarios.

Process	Economic (S1)	Environmental (S2)	Social (S3)
Sheet Extruding	0,61	0,32	0,41
Liner Forming	0,36	0,47	0,57
Cabinet Assembling	0,82	0,87	0,48
Cabinet Metal Forming	0,91	0,89	0,51
Cabinet Foaming	0,64	0,6	0,71
Refrigerant Cycle Assembling	0,89	0,95	0,82
Final Assembling	0,76	0,89	0,82

Table 6: TOPSIS scores of manufacturing processes across different sustainability scenarios

Sheet Extruding exhibits the lowest performance in both in S2 and S3, indicating a high need for improvement regarding ecological and social sustainability. In S1, it achieves a moderately low score, ranking as the second-worst performing process, further confirming its overall optimization potential. These findings highlight a significant opportunity for targeted measures to enhance its sustainability performance across multiple dimensions.

Similarly, Liner Forming shows considerable potential for improvement, especially in scenarios where economic and environmental factors receive higher emphasis, as reflected in S1 and S2. Although Liner Forming performs comparatively better in S3, which likely shifts focus toward the social dimension, its aggregate performance remains comparatively weak. This suggests that tailored interventions could effectively elevate its sustainability profile. These results clearly indicate existing improvement potential, suggesting that tailored measures could effectively enhance its sustainability profile.

In contrast, the processes Refrigerant Cycle Assembling and Final Assembling consistently achieve high performance levels across all three scenarios, positioning them as benchmarks for sustainable manufacturing practices within the case study.

The analysis of the results visualized in the heatmap underscores a need for improvement and targeted measures in several production processes to enhance their performance across economic, environmental, and social dimensions. SPDA effectively distinguishes between processes, consistently identifying those with the highest optimization potential. This reliable differentiation not only validates the algorithm’s capability to integrate multi-criteria preferences but also attests to its robustness and practical applicability as a comprehensive decision-support instrument in sustainable manufacturing contexts. Consequently, these findings reinforce the algorithm’s value in guiding strategic improvement efforts by pinpointing priority areas for sustainable development within complex production systems.

7 Conclusion and Limitations

This chapter presents the main findings of this work, discusses their implications, and reflects on the contributions made. It also addresses methodological and data-related limitations encountered during the research. Finally, directions for future development are proposed, with the aim of further advancing the presented approach.

In recent years, a variety of extended VSM approaches have been developed to address the increasing need for integrating sustainability considerations into production systems. These methods vary in scope, focus, and methodological depth, yet all aim to incorporate the TBL perspective, as summarized in Table 1. SVSM, LC-VSM, TBL-VSM, and VSM4S encompass all TBL indicators, while EVSM, GIVSM, and OGP-VSM focus solely on economic and environmental KPIs. The dominance of SVSM is particularly evident, as 31 out of the 44 relevant documents employ this methodology. To make sustainability performance measurable in manufacturing companies, sustainability KPIs were defined and measured. Based on these KPIs, the current state of a company was visualized. Some studies defined critical thresholds for sustainability KPIs and applied them within a Traffic Light System to enhance the visibility of inefficiencies in the production system.

While existing methodologies and approaches to sustainable VSM often rely heavily on expert judgment, historical data analysis, or the establishment of critical thresholds for each sustainability KPI, these processes are typically time-consuming and resource intensive. (Soltani et al., 2019) introduced the TOPSIS algorithm to systematically rank production steps based on their sustainability impact, thereby providing a quantitative foundation for prioritization. However, a research gap exists due to the absence of a practical software implementation of the TOPSIS-based prioritization method, which, although conceptually sound, was not accompanied by an operational tool.

To address this gap, the Sustainability Potential Detection Algorithm (SPDA) was developed, combining the AHP methodology with the TOPSIS algorithm to identify sustainability potentials by prioritizing production steps based on their sustainability impact. To facilitate ease of use, especially for users with limited experience in VSA, the AHP implementation employs an adapted, simplified version of Saaty's scale, as detailed in Table 2. This simplification aims to enhance usability and reduce cognitive load in the decision-making process.

A distinctive strength of SPDA lies in the incorporation of rigorous validation steps via Pydantic, which ensures that inputs are thoroughly checked for consistency and correctness before processing. These validation mechanisms serve as robust safeguards against malformed or inconsistent data, thereby enhancing the overall reliability and reproducibility of the algorithm's results.

Beyond identifying processes with potential for sustainability-oriented improvement, SPDA introduces a novel approach by systematically analyzing the influence of individual KPIs on the overall sustainability performance of each process. By quantifying the impact of each KPI on deviations from the ideal solution, and by integrating the Path Factor to indicate whether a process lies on the main path or requires additional processing steps (e.g., rework, refinement), the algorithm offers a unique diagnostic perspective that allows for precise attribution of performance deficits to specific sustainability criteria. This analytic depth facilitates root-cause analysis and supports more precise, criterion-specific intervention strategies. Together, these technical features make SPDA not only a robust decision-support tool for sustainable production but also a user-friendly and transparent system, capable of bridging the gap between complex multi-criteria decision methods and practical industrial applications.

The developed algorithm was evaluated using a case study from a refrigerator and freezer manufacturing factory, as described by (Khakpour et al., 2023). The value stream of a specific refrigerator-freezer model served as the basis for the analysis. In this case study, the sustainability performance of the production process was assessed using KPIs that reflect the three pillars of sustainability.

To test the algorithm under realistic industrial conditions, the pairwise comparison matrix was adjusted to reflect three different decision-making perspectives, resulting in scenarios S1, S2, and S3. These variations simulated typical situations in which stakeholders assign different priorities to sustainability objectives based on strategic goals or regulatory requirements. The algorithm responded effectively to these changes, producing reliable and meaningful prioritizations of production steps. This demonstrates its suitability for dynamic industrial environments, where decision-making must account for varying sustainability targets. The ability to integrate user-defined preferences in a transparent and automated manner underscores the algorithm's potential as a practical decision-support tool for sustainable production planning.

Despite the promising results achieved with SPDA, several limitations must be acknowledged. First, the AHP methodology employs a simplified form of the Saaty scale for pairwise comparisons. While this choice improves user-friendliness and consistency in the judgment matrix, it reduces the granularity of expressed preferences. As a result, nuanced or more differentiated expert judgments may not be adequately captured.

Second, CR calculation is based on Saaty's RI values, which are only defined for comparison matrices with up to 10 criteria. This restricts the use of the algorithm to decision problems involving a relatively small number of KPIs. For larger matrices, suitable RI approximations or alternative inconsistency metrics would be required.

8 Outlook and Future Work

Regarding future development, a promising extension of SPDA would be the integration of multiple expert evaluations through group decision-making frameworks. Currently, the algorithm processes a single pairwise comparison matrix representing the preferences of one decision-maker for the AHP weighting of sustainability KPIs. However, in practical industrial settings, decisions on sustainability priorities often require consensus among several experts with potentially divergent perspectives. To address this, the algorithm could be enhanced to aggregate multiple pairwise comparison matrices obtained from different experts into a collective preference structure. Established aggregation methods, such as the geometric mean of individual comparison matrices, can be employed to synthesize a consensus pairwise matrix. This aggregated matrix would then be used to derive a unified set of criterion weights, reflecting a balanced group judgment.

Furthermore, when the number of KPIs becomes very large, conducting pairwise comparisons using AHP can become impractical due to the rapidly increasing number of comparisons and the cognitive burden on experts. In such cases, a hierarchical structuring of KPIs into group clusters can significantly simplify the weighting process. For instance, when KPIs naturally group into clusters such as economic, environmental, and social dimensions, a two-level AHP approach can be applied. First, experts assess the relative importance of these main KPI clusters through pairwise comparisons, resulting in a manageable comparison matrix at the cluster level. Then, within each cluster, the KPIs are compared pairwise separately to establish local weights. Finally, the overall weights for individual KPIs are obtained by multiplying their local weights by the weight of their respective cluster. This hierarchical decomposition into group clusters reduces the number of comparisons required at each step, easing the cognitive load on experts while preserving the interpretability of the results. Moreover, distributing comparison tasks across multiple experts and aggregating their judgments further enhances the robustness and reliability of the weighting process.

Moreover, another key objective for the future development of SPDA would be the deployment of the algorithm as an online service using Docker within the SMP platform. Currently, the tool operates locally, which limits its accessibility and integration into broader digital infrastructures. By deploying the algorithm to a cloud environment and linking it directly with SMP, real-time access and scalability across various industrial use cases can be achieved. Additionally, a dedicated front-end dashboard could be developed, enabling the interactive visualization of decision-making outcomes. For instance, radar charts could be used to compare process performance across sustainability KPIs, while time-series plots could help monitor TOPSIS scores over multiple evaluations. Such visual analytics would support users in better understanding, evaluating, and communicating results more effectively.

9 Appendix

9.1 Identified sustainability KPIs through SLR

Sustainability KPIs	Equation	Legend of Abbreviations	References
Economic			
Time efficiency (%)	TE=(VAT/TT) *100%	TE: Time efficiency VAT: Value added time TT: Total time	(Utama et al., 2022), (Dewi et al., 2023), (Atoillah & Hartini, 2021), (Saraswati et al., 2024), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hudy et al., 2023), (Sari Emelia et al., 2021), (Hartini et al., 2019), (Vinodh et al., 2016), (Mubin et al., 2023), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Sari et al., 2022), (Phuong & Guidat, 2018), (Chaparin et al., 2023), (Rosiani et al., 2024), (Hartini et al., 2018), (Ikatrinasari et al., 2018)
Inventory efficiency (%)	IE = (NI/TM) *100%	IE: Inventory efficiency NI: Number of inventories TM: Total material	(Utama et al., 2022), (Dewi et al., 2023), (Marie Iveline Anne et al., 2022), , (Hartini et al., 2020; Rosiani et al., 2024)
Quality efficiency (%)	QE = (1 - (ND/TM)) *100%	QE: Quality efficiency ND: Number of defects TM: Total material	(Utama et al., 2022), (Dewi et al., 2023), (Atoillah & Hartini, 2021), (Saraswati et al., 2024), (Marie et al., 2022), (Hudy et al., 2023), (Djatna & Prasetyo, 2019), (Sari Emelia et al., 2021), (Mubin et al., 2023), (Hartini et al., 2020), (Hartini et al., 2018)
Cost efficiency (%)	CE = (VAC/TC) *100%	CE: Cost efficiency VAC: Value added cost TC: Total cost	(Utama et al., 2022), (Dewi et al., 2023), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Rosiani et al., 2024), (Hartini et al., 2018)
Operating Cost (currency per unit)	OC=CT*(LabC + MC + DC)	OC: Operating Cost CT: Cycle Time	(Swarnakar et al., 2020), (Khakpour et al., 2023)

		LabC: Labor cost MC: Management cost DC: Depreciation cost	
Overall Equipment Efficiency (%)	OEE=A*P*Q A=((LT-TD)/LT) *100% P=((IC*O)/OP) *100% Q=((TP-DP)/TP) *100%	OEE: Overall Equipment Efficiency A: Availability Rate LT: Loading Time TD: Total Downtime P: Performance Rate IC: Ideal Cycle time O: Output OP: Operating Time Q: Quality Rate TP: Total Product DP: Defect Product	(Dewi et al., 2023), (Swarnakar et al., 2020), (Rosiani et al., 2024)
Effective cost (currency per unit)	EC=OC/OEE	EC: Effective cost OC: Operating Cost OEE: Overall Equipment Efficiency	(Swarnakar et al., 2020), (Khakpour et al., 2023)
Environmental			
Material efficiency (%)	ME = (VAM/TM) *100% = = (MC/PR) *100%	ME: Material efficiency VAM: Value added material TM: Total material used MC: number of materials consumed PR: number of products released	(Utama et al., 2022), (Dewi et al., 2023), (Atoillah & Hartini, 2021), (Saraswati et al., 2024), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hudy et al., 2023), (Djatna & Prasetyo, 2019), (Mubin et al., 2023), (Hartini et al., 2020), (Rosiani et al., 2024), (Hartini et al., 2018)
Raw material consumption (kg)			(Vinodh et al., 2016), (Lindström & Ingesson, 2016), (Sari et al., 2022), (Ikatrinasari et al., 2018), (Khakpour et al., 2023)
Energy/Power consumption (kWh)			(Vinodh et al., 2016), (Lindström & Ingesson, 2016), (Antomarioni et al., 2018), (Sari et al., 2022), (Phuong & Guidat,

			2018), (Chaparin et al., 2023), (Ikatrinasari et al., 2018), (Khakpour et al., 2023), (Swarnakar et al., 2020)
Total energy consumption (mPt)			(Vinodh et al., 2016)
Energy efficiency (%)	EE = (VAE/TE) *100% = (EP/TE) *100%	EE: Energy efficiency VAE: Value added energy TE: Total energy EP = Amount of energy used for production	(Utama et al., 2022), (Dewi et al., 2023), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hudy et al., 2023), (Mubin et al., 2023), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Rosiani et al., 2024), (Hartini et al., 2018)
Efficiency of waste recycling (%)	WE = (1 - (WL/TW)) *100%	WE: Waste recycling Efficiency TW: Total waste WL: Number of wastes to landfill	(Utama et al., 2022), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Sari et al., 2022)
Water Consumption/Efficiency (%)	WE=(AW/TW) *100%	WE: Water Consumption/Efficiency AW: Amount of Water TW: Total Water	(Dewi et al., 2023), (Marie Iveline Anne et al., 2022), (Swarnakar et al., 2020), (Hudy et al., 2023), (Djatna & Prasetyo, 2019), (Vinodh et al., 2016), (Mubin et al., 2023), (Lindström & Ingesson, 2016), (Utama & Abirfatin, 2023), (Phuong & Guidat, 2018), (Rosiani et al., 2024), (Ikatrinasari et al., 2018)
Waste water recycling (%)	WE=(WR/TW) *100%	WE: Waste water recycling efficiency WR: Waste recycling TW: Total waste	(Saraswati et al., 2024), (Sari Emelia et al., 2021)
Waste Generation (%)	WGE_{eff}=(WG_{act}/WG_{max})* 100%	WGE_{eff}: Waste generation efficiency WG_{act}: Actual waste generation value WG_{max}: highest waste generation is	(Rosiani et al., 2024), (Khakpour et al., 2023)

		considered the worst performance	
B_3 Consumption (%)	BB=(TB/FN) *100%	BB: Raw materials that are hazardous TB: Total weight of hazardous raw materials FN: Normal Factor (normal weight of the product)	(Dewi et al., 2023)
Land Use (%)	LT=(LA/TL) *100%	LT: Land Covered LA: Building Covered Area TL: Total Manufacturing Area	(Dewi et al., 2023)
Carbon footprint (mPt)			(Vinodh et al., 2016)
Water eutrophication (mPt)			(Vinodh et al., 2016)
Air acidification (mPt)			(Vinodh et al., 2016)
Oil and coolant consumption (Liters)			(Vinodh et al., 2016)
Emitted carbon dioxide CO_2l (kg)			(Antomarioni et al., 2018)
Overall Environmental Equipment Effectiveness (dimensionless)			(Antomarioni et al., 2018)

Social			
Satisfaction level (%)	Sat_L = (1 - (TO/NE)) *100%	Sat_L: Satisfaction level TO: Number of employee turnover NE: Number of employees	(Utama et al., 2022), (Dewi et al., 2023), (Saraswati et al., 2024), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hudy et al., 2023), (Sari Emelia et al., 2021), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Rosiani et al., 2024)
Health level (%)	HL = (1 - (NA/NE)) *100%	HE: Health level NA: Number of absent employees NE: Number of employees	(Utama et al., 2022), (Dewi et al., 2023), (Atoillah & Hartini, 2021), (Hudy et al., 2023), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Sari et al., 2022), (Rosiani et al., 2024), (Hartini et al., 2018)
Absent rate (dimensionless)	AbsR=TAT/TWT	AbsR: Absent rate TAT: total absentee time (in h) TWT: total working time (in h)	(Swarnakar et al., 2020), (Khakpour et al., 2023)
Safety level (%)	Saf_L = (1 - (NR/Nac)) *100%	Saf_L: Safety level NR: Number of activities with risk Nac: Number of activities	(Utama et al., 2022), (Dewi et al., 2023), (Atoillah & Hartini, 2021), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Sari et al., 2022), (Rosiani et al., 2024), (Hartini et al., 2018)
Accident rate (dimensionless)	AR=NoA/NoW	AR: Accident rate NoA: Number of accidents NoW: Number of working employees	(Swarnakar et al., 2020), (Khakpour et al., 2023)
Employee training level (%)	E_TL = (NT/NE) *100%	E_TL: Employee training level NT: Number of employees who attended the training	(Utama et al., 2022), (Dewi et al., 2023), (Saraswati et al., 2024), (Marie et al., 2022), (Marie Iveline Anne et al., 2022), (Hudy et al., 2023), (Sari Emelia et al., 2021), (Hartini et al., 2020), (Utama & Abirfatin, 2023), (Rosiani et al., 2024), (Khakpour et al., 2023)

		NE: Number of employees	
Mental Load (dimensionless)	MLIE=1 - (Score of NASA TLX/max NASA TLX)	MLIE: Mental Load Index efficiency	(Dewi et al., 2023), (Mubin et al., 2023), (Utama & Abirfatin, 2023), (Rosiani et al., 2024)
Physical Load (dimensionless)	PLIE=1 - (Score of PLI/max Score PLI)	PLIE: Physical Load Index efficiency PLI: Physical Load Index	(Dewi et al., 2023), (Djatna & Prasetyo, 2019), (Vinodh et al., 2016), (Mubin et al., 2023), (Utama & Abirfatin, 2023), (Phuong & Guidat, 2018), (Rosiani et al., 2024)
Noise Level (dB)			(Marie Iveline Anne et al., 2022), (Atoillah & Hartini, 2021), (Saraswati et al., 2024), (Khakpour et al., 2023), (Sari Emelia et al., 2021), (Vinodh et al., 2016), (Sari et al., 2022), (Phuong & Guidat, 2018), (Khakpour et al., 2023)
Lighting Level (Lux)			(Sari Emelia et al., 2021)
Work environmental risks (dimensionless)			(Vinodh et al., 2016)
Overall sustainability Performance			
Economic index (%)	$Ec\_I = \Sigma w_i * E_i$	Ec_I: Economic index w_i: weight of economic indicator i E_i: score of economic indicator i	(Dewi et al., 2023), (Marie et al., 2022), (Hartini et al., 2020)
Environment index (%)	$En\_I = \Sigma w_i * V_i$	En_I: Environment index w_i: weight of environment indicator i V_i: score of environment indicator i	(Dewi et al., 2023), (Marie et al., 2022), (Hartini et al., 2020)

Environmental Performance Index (%)	EPI= Sustainability *100 % Sustainability=1-(Environmental impact of the workstation state)/(Total environmental impact of initial state production)	EPI: Environmental Performance Index	(Antomarioni et al., 2018)
Social index (%)	$S\_I=\Sigma w_i*S_i$	S_I: Social index w_i: weight of social indicator i S_i: score of social indicator i	(Dewi et al., 2023), (Marie et al., 2022), (Hartini et al., 2020)
Manufacturing sustainability index (%)	$MSI=\alpha* Ec\_I + \beta* En\_I + \gamma* S\_I$	α: weight of economic dimension β: weight of environment dimension γ: weight of social dimension	(Dewi et al., 2023), (Marie et al., 2022), (Hartini et al., 2020)

Table 7: Identified sustainability KPIs through SLR

9.2 Relevant Publications identified through SLR

First Autor	Year	Methodologies	Application areas	Dimensions of sustainability	Identification of sustainability bottlenecks and potentials
Antomarioni	2018	SVSM	Food Production	Economic, environmental	Manual
Aouag	2023	SVSM	Renewable Energy & Environmental Industries	Economic, environmental, social	Algorithm
Atoillah	2021	SVSM	Wood and Furniture	Economic, environmental, social	Setting critical targets for sustainability KPIs
Chavez	2023	TBL-VSM	Pharmaceutical and Chemical Industry	Economic, environmental	Manual
Choudhary	2019	GIVSM	Packaging and Labelling Industries	Economic, environmental	Manual
Chaparin	2023	SVSM	Food Production	Economic, environmental	Manual
Dewi	2023	SVSM	Automotive Industry	Economic, environmental, social	Setting critical targets for sustainability KPIs
Djatna	2019	SVSM	Food Production	Economic, environmental, social	Manual
Edtmayr	2016	SVSM	Automotive Industry	Economic, environmental	No
Ferrazzi	2023	SVSM	Automotive Industry	Economic, environmental	Setting critical targets for sustainability KPIs
Hartini	2019	SVSM	Wood and Furniture	Economic, environmental, social	Setting critical targets for sustainability KPIs
Hartini	2019	LC-VSM	Food Production	Economic, environmental, social	Manual
Hartini	2018	SVSM	Wood and Furniture	Economic, environmental, social	Manual
Helleno	2017	SVSM	Metals and Plastics Industries	Economic, environmental, social	Manual

First Autor	Year	Methodologies	Application areas	Dimensions of sustainability	Identification of sustainability bottlenecks and potentials
Horsthofer-Rauch	2021	LC-VSM	Concept	Economic, environmental, social	No
Horsthofer-Rauch	2024	LC-VSM	Mechanical Engineering and Manufacturing	Economic, environmental, social	No
Hudy	2023	SVSM	Mechanical Engineering and Manufacturing	Economic, environmental, social	No
Ikatrinasari	2018	SVSM	Mechanical Engineering and Manufacturing	Economic, environmental	Manual
Jamil	2020	SVSM	Metals and Plastics Industries	Economic, environmental, social	Manual
Kalemkerian	2024	CVSM	Food Production	Economic, environmental	Manual
Khakpour	2023	SVSM	Mechanical Engineering and Manufacturing	Economic, environmental, social	Manual
Kluczek	2020	LC-VSM	Food Production	Economic, environmental	Manual
Larsson	2024	SVSM	Renewable Energy & Environmental Industries	Economic, environmental, social	Setting critical targets for sustainability KPIs
Li	2017	EVSM	Renewable Energy & Environmental Industries	Economic, environmental	Manual
Lindström	2016	SVSM	Automotive Industry	Economic, environmental, social	No
Litos	2017	EVSM	Construction Materials	Economic, environmental	Manual
Marie	2022	SVSM	Automotive Industry	Economic, environmental, social	Setting critical targets for sustainability KPIs
Marie Iveline Anne	2022	SVSM	Consumer Goods and Apparel	Economic, environmental, social	Setting critical targets for sustainability KPIs
Mubin	2022	SVSM	Metals and Plastics Industries	Economic, environmental, social	Setting critical targets for sustainability KPIs

First Autor	Year	Methodologies	Application areas	Dimensions of sustainability	Identification of sustainability bottlenecks and potentials
Muñoz-Villamizar	2019	OGP-VSM	Automotive Industry	Economic, environmental	Manual
Phuong	2018	SVSM	Consumer Goods and Apparel	Economic, environmental, social	Manual
Rosiani	2023	SVSM	Construction Materials	Economic, environmental, social	Setting critical targets for sustainability KPIs
Salvador	2021	LC-VSM	Construction Materials	Economic, environmental	Manual
Samant	2020	LC-VSM	Mechanical Engineering and Manufacturing	Economic, environmental	Manual
Saraswati	2024	SVSM	Mechanical Engineering and Manufacturing	Economic, environmental, social	Setting critical targets for sustainability KPIs
Sari	2021	SVSM	Automotive Industry	Economic, environmental, social	Setting critical targets for sustainability KPIs
Sari	2022	SVSM	Metals and Plastics Industries	Economic, environmental, social	Manual
Serafim Silva	2024	VSM4S	Mechanical Engineering and Manufacturing	Economic, environmental, social	Algorithm
Soltani	2019	SVSM	Metals and Plastics Industries	Economic, environmental, social	Algorithm
Swarnakar	2020	SVSM	Automotive Industry	Economic, environmental, social	Manual
Swarnakar	2021	SVSM	Automotive Industry	Economic, environmental, social	Manual
Utama	2023	SVSM	Food Production	Economic, environmental, social	Setting critical targets for sustainability KPIs
Utama	2022	SVSM	Wood and Furniture	Economic, environmental, social	Setting critical targets for sustainability KPIs
Vinodh	2015	SVSM	Automotive Industry	Economic, environmental, social	Manual

Table 8: Relevant Publications identified through SLR

9.3 Source Code of SPDA

```
from fastapi import FastAPI

from pydantic import BaseModel, model_validator

from typing import Self

from typing import Annotated

from typing import List

from typing import Union

from fractions import Fraction

import numpy as np

import math


app = FastAPI(title="SPDA API")


# Input data model

class SPDAInput(BaseModel):

    kpi_count: Annotated[int, "Number of sustainability KPIs"]

    process_count: Annotated[int, "Number of processes"]

    pairwise_rankings: Annotated[List[List[Union[float, str]]], "pairwise
comparison matrix"]

    kpi_values:  Annotated[List[List[float]],  "Value  of  sustainability
KPIs"]

    benefit_criterias: Annotated[List[int], "1 = maximize, 0 = minimize"]

    path_factor: Annotated[List[float], "Pathfactor"]


#  AHP  method:  Validation  of  the  pairwise  comparison  matrix  -  shape,
diagonal elements and reciprocal values

    @model_validator(mode="after")

    def validate_pairwise_rankings(self) -> Self:

        check_matrix_shape(self.pairwise_rankings,       (self.kpi_count,
self.kpi_count), "pairwise_rankings")
```

```
        for i in range(self.kpi_count):

            if self.pairwise_rankings[i][i] != 1.0:

                raise  ValueError(f"pairwise_rankings[{i}][{i}]  must  be
1")

            for j in range(i + 1, self.kpi_count):

                if                                                  not
math.isclose(float(Fraction(str(self.pairwise_rankings[i][j]))),

                                    1                               /
float(Fraction(str(self.pairwise_rankings[j][i])))):

                    raise  ValueError(f"pairwise_rankings[{i}][{j}]  must
be the reciprocal of [{j}][{i}]")

        return self



# TOPSIS algorithm: Check if the decision matrix has exactly as many rows
and columns as expected;

# rows = number of processes, columns = number of criteria (sustainability
KPIs)

    @model_validator(mode="after")

    def check_kpi_values(self) -> Self:

        check_matrix_shape(self.kpi_values,          (self.process_count,
self.kpi_count), "kpi_values")

        return self

    # Check if the benefit_criterias list has exactly the same length as
the number of criteria (sustainability KPIs)

    @model_validator(mode="after")

    def check_benefit_criterias(self) -> Self:

        if len(self.benefit_criterias) != self.kpi_count:

            raise ValueError("benefit_criterias must have the same length
as kpi_count")

        # check values, if benefit_criterias list contains only values "0"
or "1"

        for i in range(self.kpi_count):
```

```
            if self.benefit_criterias[i] not in [0, 1]:

                raise        ValueError(f"benefit_criteria[{i}]        =
{self.benefit_criterias[i]} must be 0 or 1")

        return self

    # Check if the pathfactor list has exactly the same length as the
number of processes

    @model_validator(mode="after")

    def check_path_factor(self) -> Self:

        if len(self.path_factor) != self.process_count:

            raise ValueError("path_factor must have the same length as
process_count")

        return self



# Output data model

class SPDAOutput(BaseModel):

    input: Annotated[SPDAInput, "Original Input data"]

    scores: Annotated[List[float], "TOPSIS scores of processes"]

    consistency_ratio: Annotated[float, "AHP consistency ratio"]

    explanations:  Annotated[List[str],  "Explanations  of  KPIs  with
significant influence on sustainable performance and Pathfactor"]



# Check if the number of scores (TOPSIS results) exactly matches the number
of processes (process_count)

@model_validator(mode="after")

def check_scores(self) -> Self:

    if len(self.scores) != self.input.process_count:

        raise  ValueError("scores  must  have  the  same  length  as
process_count")

    return self

# check_matrix_shape is a auxiliary function that strictly verifies if the
matrices have the correct size,
```

```
# for example, whether pairwise_rankings is a square matrix of size kpi_count x kpi_count,

# and whether kpi_values has the size process_count x kpi_count

def check_matrix_shape(matrix: list[list[float]], shape: tuple[int, int], name: str) -> None:

    """

    Check if the given 2D matrix has the correct shape.

    """

    if len(matrix) != shape[0]:

        raise ValueError(f"{name} must have {shape[0]} rows")

    for row in matrix:

        if len(row) != shape[1]:

            raise ValueError(f"{name} must have {shape[1]} columns")



# AHP method

# Calculation of the weights

def calculate_weights_from_input(input_data):

    matrix = np.array(input_data.pairwise_rankings)

    column_sums = np.sum(matrix, axis=0)

    normalized_matrix = matrix / column_sums

    weights = np.mean(normalized_matrix, axis=1)

    return normalized_matrix, weights

# Converts all elements in the pairwise comparison matrix to floats.

def parse_pairwise_matrix(matrix):

    return [[float(Fraction(cell)) if isinstance(cell, str) else float(cell) for cell in row] for row in matrix]

# Consistency analysis

def consistency_analysis(matrix):

    matrix = np.array(matrix)

    n = matrix.shape[0]
```

```
    eigvals, _ = np.linalg.eig(matrix)

    lambda_max = np.max(eigvals).real  # only real component

    CI = (lambda_max - n) / (n - 1)

    RI = {1: 0.00, 2: 0.00, 3: 0.58, 4: 0.90, 5: 1.12, 6: 1.24,

          7: 1.32, 8: 1.41, 9: 1.45, 10: 1.49}  # Saaty RI, valid only for
kpi_count up to 10

    CR = CI / RI.get(n, 1) if RI.get(n, 1) > 0 else 0

    return lambda_max, CI, CR


# TOPSIS algorithm

def topsis(input_data, weights):

    decision_matrix = np.array(input_data.kpi_values, dtype=np.float64)

    benefit_criteria = np.array(input_data.benefit_criterias)

    # Normalization of decision matrix

    column_norms = np.sqrt(np.sum(np.square(decision_matrix), axis=0))

    column_norms[column_norms == 0] = 1 # Prevents division by zero

    normalized_matrix = decision_matrix / column_norms

    # Weighting

    weighted_matrix = normalized_matrix * weights

    # Ideal- und Anti-Ideal solution

    ideal_solution = np.max(weighted_matrix, axis=0) * benefit_criteria +
np.min(weighted_matrix, axis=0) * (1 - benefit_criteria)

    anti_ideal_solution    =    np.min(weighted_matrix,    axis=0)    *
benefit_criteria    +    np.max(weighted_matrix,    axis=0)    *    (1    -
benefit_criteria)

   # Distance to Ideal/Anti-Ideal solution of each criteria

    distance_to_ideal = np.sqrt(np.sum((weighted_matrix - ideal_solution)
** 2, axis=1))

    distance_to_anti_ideal    =    np.sqrt(np.sum((weighted_matrix    -
anti_ideal_solution) ** 2, axis=1))

    # TOPSIS-Scores

    topsis_scores   =   distance_to_anti_ideal   /   (distance_to_ideal   +
distance_to_anti_ideal)
```

```
    return     topsis_scores,     normalized_matrix,     weighted_matrix,
ideal_solution, anti_ideal_solution

# KPI Influence Analysis

def        analyze_kpi_influence(weighted_matrix,        ideal_solution,
anti_ideal_solution):

    num_processes = weighted_matrix.shape[0]

    influence_ideal = np.zeros_like(weighted_matrix)

    influence_anti_ideal = np.zeros_like(weighted_matrix)

    for i in range(num_processes):

        diff_ideal = (weighted_matrix[i] - ideal_solution) ** 2

        diff_anti = (weighted_matrix[i] - anti_ideal_solution) ** 2

        sum_diff_ideal = np.sum(diff_ideal) if np.sum(diff_ideal) > 0 else
1

        sum_diff_anti = np.sum(diff_anti) if np.sum(diff_anti) > 0 else 1

        influence_ideal[i] = diff_ideal / sum_diff_ideal

        influence_anti_ideal[i] = diff_anti / sum_diff_anti


    return influence_ideal.tolist(), influence_anti_ideal.tolist()

#Interpretive Explanations

def generate_explanations(scores, influence_ideal, path_factor):

    explanations = []

    for i, score in enumerate(scores):

        if score <= 0.50:

            influencing_kpis = [

                f"KPI {j}" for j, value in enumerate(influence_ideal[i])
if value >= 0.25

            ]

            if influencing_kpis:

                cause = ", ".join(influencing_kpis)

            else:

                cause = "is not significantly influenced by any KPI"
```

```
            explanations.append(
                f"Process {i} exhibits a low degree of conformity with the ideal solution - Improvement potential -> {cause} -> PathFactor={path_factor[i]}."
            )
        elif 0.51 <= score <= 0.75:
            influencing_kpis = [
                f"KPI {j}" for j, value in enumerate(influence_ideal[i]) if value >= 0.25
            ]
            if influencing_kpis:
                cause = ", ".join(influencing_kpis)
            else:
                cause = "is not significantly influenced by any KPI"
            explanations.append(
                f"Process {i} demonstrates a moderate degree of conformity with the ideal solution - Improvement potential -> {cause} -> PathFactor={path_factor[i]}."
            )
        else:
            explanations.append("")  # Skip explanations for processes with scores > 0.76
    return explanations


@app.post("/run-SPDA", response_model=SPDAOutput)
def run_SPDA3(input_data: SPDAInput):
    # AHP Weighting
    pairwise_matrix = np.array(parse_pairwise_matrix(input_data.pairwise_rankings))
    _, weights = calculate_weights_from_input(
        input_data.model_copy(update={"pairwise_rankings": pairwise_matrix.tolist()})
    )
```

```
    # Consistency analysis
    n = input_data.kpi_count
    eigvals, _ = np.linalg.eig(pairwise_matrix)
    lambda_max = np.max(eigvals).real
    CI = (lambda_max - n) / (n - 1) if n > 1 else 0
    RI = {1: 0.00, 2: 0.00, 3: 0.58, 4: 0.90, 5: 1.12, 6: 1.24,
          7: 1.32, 8: 1.41, 9: 1.45, 10: 1.49}
    CR = CI / RI.get(n, 1) if RI.get(n, 1) > 0 else 0


    # Execution of TOPSIS
    scores, _, weighted_matrix, ideal_solution, anti_ideal_solution =
topsis(input_data, weights)


    # Impact analysis
    influence_ideal, influence_anti_ideal =
analyze_kpi_influence(weighted_matrix, ideal_solution,
anti_ideal_solution)


    # Explanations
    explanations = generate_explanations(scores, influence_ideal,
input_data.path_factor)


    # Return API result
    return SPDAOutput(
        input=input_data,
        scores=[round(s, 2) for s in scores.tolist()],
        consistency_ratio=round(CR, 2),
        explanations=explanations
    )
```

Figure 56: Source Code of SPDA

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14 List of abbreviations

%	Percent
ABS	Acrylonitrile Butadiene Styrene
AHP	Analytic Hierarchy Process
API	Application Programming Interface
AR	Accident Rate
B/C	Benefit-Cost ratio
CI	Consistency Index
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
COP	Conference of Parties
CR	Consistency Ratio
CRB	Circular Resource Box
CRMA	Critical Raw Material Act
CVSM	Circular Value Stream Mapping
dB(A)	A-weighted decibel
DMAIC	Define, Measure, Analyze, Improve, Control
e.g.	for example
EC	Energy Consumption
EDAS	Evaluation Based on Distance from Average Solution
EGD	European Green Deal
EPEI	Every Part Every Interval
ERFMI	European Resilient Flooring Manufacturers' Institute
ERP	Enterprise Resource Planning
etc.	et cetera
EU	European Union
EVSM	Environmental Value Stream Mapping
FMEA	Failure Mode and Effects Analysis
FTE	Full-Time equivalent
GDIP	Green Deal Industrial Plan
GHG	Greenhouse Gas
GIVSM	Green-Integrated Value Stream Mapping
GRI	Global Reporting Initiative
HDI	Human Development Index
HR	Human Resources
i.e.	that is

IDE	Integrated Development Environment
ISEW	Index of Sustainable Economic Welfare
IT	Inventory Time
JSON	JavaScript Object Notation
Kg	Kilograms
KPI	Key Performance Indicator
kWh	Kilowatt hours
LC	Life Cycle
LCA	Life Cycle Assessment
LCC	Life Cycle Costing
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessments
LoC	Level of Consensus
LT	Lead Time
MC	Material Consumption
MCDM	Multi-Criteria Decision Making
MDI	Methylene Diphenyl Diisocyanate
MES	Manufacturing Execution System
MSI	Manufacturing Sustainability Index
NDC	Nationally Determined Contributions
NL	Noise Level
NZIA	Net-Zero Industry Act
OBC	Operator Balance Chart
OGP	Overall Greenness Performance
P	Polyol
P&L	Profit and Loss
PC	Process Costs
PDCA	Plan, Do, Check, Act
REBA	Rapid Entire Body Assessment
RI	Random Index
SBTi	Science Based Targets initiative
SDGs	Sustainable Development Goals
sec	Seconds
SI	Sustainability Index
SIE_c	Sustainability Index for Economic factors
SIE_n	Sustainability Index for Environmental factors
SIPOC	Supplier, Input, Process, Output, Customer
SIS_c	Sustainability Index for Social factors
SLCA	Social Life Cycle Assessment

SLR	Systematic Literature Review
SLSS	Sustainable Lean Six-Sigma
SM	Skilled Manpower
SMED	Single Minute Exchange of Die
SMP	Sustainable Monitoring Platform
SPC	Statistical Process Control
SPDA	Sustainability Potentials Detection Algorithm
SSIS	Synthetic Sustainability Indicator of the System
SVSM	Sustainable Value Stream Mapping
TBL	Tripple Bottom Line
TLS	Traffic Light System
TOPSIS	Technique for Order Preference by Similarity to the Ideal Solution
TPM	Total Productive Maintenance
TPS	Toyota Production System
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
VSA	Value Stream Analysis
VSD	Value Stream Design
VSM	Value Stream Mapping
WA	Weighted Average
WoEC	Waste of Energy Consumption