DEPARTAMENT OF
MECHANICAL AND INDUSTRIAL ENGINEERING

DECISION SUPPORT SYSTEM FOR PRODUCTION PLANNING FROM A SUSTAINABILITY PERSPECTIVE

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"Your task is not to foresee the future,

but to enable it."

Antoine de Saint Exupéry, Citadelle, 1948

ABSTRACT

Manufacturing enterprises supply our global demand for products, creating economic value. Moreover, they are also responsible for several environmental and social impacts, e.g., greenhouse gases, waste, and poor working conditions. These impacts cause climate change, air and sea pollution, and social inequality, which are a few examples of current challenges for global sustainability strategies. However, researchers have widely addressed these impacts and warned politicians and society about the risk of the collapse of ecosystems.

Despite these warnings, manufacturing enterprises still have difficulties improving the sustainability of their production processes. Therefore, new technologies are required to support enterprises and help determine their production processes' sustainability status by considering multiple aspects (economic, environmental, and social). Moreover, advice should be given on how the identified issues can be avoided, reduced, or compensated for future production activities.

This research presents a fuzzy decision support system and an experimental study for sustainability-based production planning. For this approach, systematic literature reviews were made, analysing concept methods for sustainability-based production management and planning. The results show, among other things, that current methods for sustainability-production planning are focused on single aspects of sustainability (e.g., energy or waste planning). Therefore, a fuzzy decision support system was developed that simultaneously evaluates social, environmental, and economic aspects. The decision support system's model identifies the most significant opportunities to improve the production program's sustainability and gives recommendations on how to change it.

The decision support system was tested and validated in an experimental study in the production planning laboratory at Emden University of Applied Sciences. The study results discuss problems, needs, and challenges affecting sustainability-based production planning. Moreover, opportunities for future research were identified based on the limitations of the experimental study.

Keywords: Sustainable Development; Sustainability; Sustainable Manufacturing; Production Planning; Decision Support System Fuzzy Logic

Resumo

As empresas transformadoras satisfazem a procura global de produtos, criando valor económico. No entanto, também são responsáveis por vários impactos ambientais e sociais, por exemplo, gases de efeito estufa, resíduos e más condições de trabalho. Estes impactos originam alterações climáticas, poluição do ar e do mar e desigualdade social, que constituem alguns exemplos dos desafios que se colocam atualmente às estratégias globais de sustentabilidade. De notar que os investigadores têm abordado amplamente estes impactos e alertado os políticos e a sociedade sobre o risco do colapso dos ecossistemas.

Apesar destes alertas, as empresas transformadoras ainda têm dificuldades em melhorar a sustentabilidade dos seus processos produtivos. Como tal, são necessárias novas tecnologias para apoiar as empresas, ajudando a caracterizar o estado de sustentabilidade dos seus processos de produção, considerando múltiplos fatores (económicos, ambientais e sociais). Além disso, devem ser dados conselhos sobre o modo como os problemas identificados podem ser evitados, reduzidos ou compensados em atividades de produção futuras.

A investigação realizada contribuiu para o desenvolvimento de um sistema de apoio à decisão difuso, aplicado a um estudo de caso de planeamento da produção baseado na sustentabilidade. Para o efeito, foram conduzidas revisões sistemáticas da literatura, analisando os conceitos associados aos métodos para gestão e planeamento da produção baseado na sustentabilidade. Os resultados revelam, entre outras conclusões, que os métodos atuais para o planeamento da produção sustentável estão focados em fatores isolados de sustentabilidade (e.g., planeamento energético ou de resíduos). Perante este contexto, foi desenvolvido um sistema de apoio à decisão difuso, que avalia simultaneamente fatores sociais, ambientais e económicos. O modelo do sistema de apoio à decisão identifica as oportunidades mais significativas para melhorar a sustentabilidade do programa de produção e fornece recomendações sobre o modo como este pode ser alterado. O sistema de apoio à decisão foi testado e validado num estudo de caso simulado no laboratório de planeamento da produção na Universidade de Ciências Aplicadas de Emden. Os resultados do estudo de caso permitiram analisar os problemas, necessidades e desafios que afetam o planeamento da produção baseado na sustentabilidade. Complementarmente, foram identificadas oportunidades de investigação futuras, considerando as limitações do estudo de caso realizado.

Palavas chave: Desenvolvimento Sustentável; Sustentabilidade; Produção Sustentável; Planeamento da Produção; Sistema de Apoio à Decisão; Lógica Difusa

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ACRONYMS

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
COPRAS	Complex Proportional Assessment of Alternatives
CRU	Use of Recycled Carrier
DEMANTEL	Decision-Making Trial and Evaluation Laboratory
ELECTRE	Elimination Et Choix Traduisant la Realité
EPA	Environmental Protection Agency
ERP	Enterprise resource planning
FIM	Fuzzy inference model
GHG	Greenhouse gas
ICPP	Intergovernmental Panel on Climate Change
IO	Input-Output
ISM	Interpretive Structural Modelling
M2B	Machines to business process communication
M2M	Machine to machine communication
NIST	National Institute of Standards and Technology
NSGA	Nondominated Sorting Genetic Algorithm
PLC	Programmable logic controller
PO	Total Product Output
PROMETHEE	Preference Ranking Organisation Method for Enrichment Evaluations
PSD	Preference Set-based Design
QT_PP	Average Production Queue Time
QT_WH	Average Warehouse Queue Time
REU	Renewable Energy Usage
RQ	Research Question
SBSC	Sustainability Balanced Scorecard
SDG	Sustainable Development Goals
SoS	System of Systems
TBL	Triple bottom line
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UN	United Nations
UNCCC	UN Climate Change Conference
UNCSD	UN Conference on Sustainable Development
WL	Accumulated Work Load Peak
WSM	Weighted Sum Model

1 INTRODUCTION

Globalization currently faces the challenge of meeting the continuously growing worldwide demand for manufactured products and goods while simultaneously ensuring sustainable development (Stock and Seliger, 2016). However, considering that the terms "sustainability" and "sustainable development" have no standard definitions, it is necessary to clarify what they mean in sustainable manufacturing practices.

The Brundtland Report by the World Commission on Environment and Development proposed a still widely applied definition of sustainable development: "development which meets the needs of current generations without compromising the ability of future generations to meet their own needs" (WCED, 1987). Another widely accepted concept of sustainability is the triple bottom line (TBL) proposed by Elkington (Elkington, 2007). This concept has been used in several studies and describes sustainability as a balance of economic, environmental, and social pillars. According to these widely accepted definitions and concepts, sustainable system development can only be achieved if the needs of current and future generations of humans are considered in terms of the three pillars of sustainability: economic, environmental, and social.

The global problems and need for sustainability have been presented by researchers in numerous reports in the last five decades, such as the study "Limit of Growths" (Meadows et al., 2004; Meadows, 1974) or the Intergovernmental Panel on Climate Change's (ICPP) special report "Global Warming of 1.5 °C" (Masson-Delmotte et al., 2018). Moreover, the United Nations (UN) has acknowledged the need for sustainability and has organized yearly conferences to discuss political goals and actions. The results of this initiative include the Paris Agreement from the 2015 UN Climate Change Conference (UNCCC) in Paris (United Nations, 2015a) and the 2030 Agenda for the Sustainable Development Goals (SDGs) from the 2015 UN Conference on Sustainable Development (UNCSD) in New York (United Nations, 2015c). Consumer expectations are also changing, and sustainability concerns affect buying decisions. An increasing number of consumers are concerned with, for example, product origin, fair payment, and animal welfare (handelsjournal, 2019). Despite warnings from researchers, favourable political framework conditions, and changing consumer expectations, enterprises still have difficulties improving the sustainability of their production processes. The problems include, for instance, the high-effort nature and the complexity of strategic, tactical, and operative sustainability-based production management (Bhanot et al., 2017).

Enterprise development is generally achieved through strategic, tactical, and operational production management to create economic value, such as investment in production capacities, material selection, and resource scheduling (Stock and Seliger, 2016). Sustainable enterprise development requires additional strategic and tactical planning efforts for new or existing production processes, such as investments in on-site renewable energy supplies, the integration of recycling processes, and an ergonomic design of workplaces. Operational production management (so-called production planning) involves planning and controlling the actual production activities within these framework conditions to produce an expected production output as sustainable as possible through (Sun et al., 2022), for example, demanding available renewable energy, avoiding waste, and reducing occupational risks. A production planning system supports production schedulers in planning production processes—accepting customer orders, controlling the transformation process of materials to products, and delivering the products to the customers (Gronau, 2014). Conventional production planning is a complex task because many factors of a production system contribute to its planning processes, such as machine failures, breakdowns, and a lack of materials. Addressing additional sustainability goals, such as limits for emissions, renewable resource usage, and social issues, makes production planning much more effortful and complex (Giret et al., 2015; Hemdi et al., 2013).

Decision support systems offer one opportunity to assist sustainability-based production planning by helping decision-makers in operational, tactical, and strategic production management activities (Turban et al., 2005). In a sustainability problem context, relevant data, information, and knowledge are collected, prepared, and evaluated, focusing on sustainability goals. Based on the evaluation results, recommendations are given by the decision support system to the decision-maker(s) regarding operative decisions that improve sustainability aspects. Therefore, decision support systems can be used to reduce the burden and complexity of production planning through the consideration of additional sustainability goals (Akbar and Irohara, 2018; Giret et al., 2015; Vorderwinkler and Heiss, 2011).

This research aims to develop and implement a decision support system for sustainability-based production planning considering economic, environmental, and social aspects. For this approach, the following research questions (RQ) have been defined:

RQ 1. How can production systems be evaluated considering all three sustainability dimensions (economic, environmental, and social) for production planning purposes?

RQ 2. What additional information needs to be collected for decision-making in sustainability-based production planning processes?

RQ 3. How can a decision support system use this data and information to evaluate and improve the sustainability of the production system with the aid of production planning?

The main structure of the document is as follows. The research methodology is presented in Section 2, followed by literature reviews in Section 3. The concept of the decision support system for sustainability-based production planning is described in Section 4. Based on this concept, Section 5 presents the implementation and concept proof of the decision support system. The research results are validated in Section 6. The conclusion and future work of the thesis are presented in Section 7, followed by a list of references and an appendix.

2

Research Methodology

For sustainability impacts, such as climate change, violation of human rights, contamination of water, humans are both the leading causes of all these issues and those who must find solutions to solve them (Thatcher, 2016). These solutions must avoid, minimize, or compensate impacts on local and global systems according to environmental and economic aspects and meet the needs and wellbeing of current generations living in these local and global systems, without compromising the needs and wellbeing of future generations. According to these adapted definitions from the Brundtland report and the TBL concept, it is obvious that affected humans play a major role in new solutions and thus in supporting sustainable system development.

Therefore, the research methodology for developing the decision support system for sustainability-based production planning and answering the RQs is adapted from the standard for the human-centred design of computer-based interactive systems (ISO 9241-210:2010). Figure 2.1 shows an overview of the relationship between the research methodology and the main sections, phases, methods, and outcomes of the thesis. The research methodology consists of six iterative phases:

1. Identifying the needs of the decision support system,
2. Specifying the context of decision-making,
3. Specifying the decision support system framework conditions,
4. Designing and implementing the decision support system,
5. Testing the decision support system, and
6. Evaluating the research results.

In phase 1 **(identifying the needs of the decision support system)**, related literature was searched and reviewed following narrative literature review procedures. This phase followed mainly a constructive research principles combing knowledge for production planning, sustainability, and decision-making. The main outcome of these literature reviews is the definition of the problem statement and the first RQs.

In phase 2 **(specifying the context of decision-making)**, the decision context and environment were determined by analyzing the state of the art. For this approach, first, narrative literature reviews were conducted to discuss existing definitions and concepts for the terms sustainability, sustainable manufacturing, and sustainability-based production planning. Second, systematic literature reviews were performed to overview the theoretical background and related literature about sustainability-based production planning and decision-making using fuzzy logic to answer RQ 1.

In phase 3 **(specifying the decision support system framework conditions)**, the framework conditions of the decision support system for sustainability-based production planning were set. For this approach, the sustainable system of systems (SoS) proposed in Thatcher (2016) was adapted to identify the effects and impacts of stakeholder interests for sustainable manufacturing on affected systems.

In phase 4 **(design and implementation of the decision support system)**, the decision support system concept was developed and implemented based on the framework conditions identified through the adapted SoS approach. The concept consists of three elements:

1. Variable and goal collections for sustainability-based production planning,
2. A fuzzy inference model for the decision-making process, and
3. A user interface for sustainability-based production planning.

The collection of variables and goals was developed based on existing databases for sustainability purposes and existing models for sustainability-based production planning to answer RQ 2. The fuzzy inference model was developed using theoretical background information for fuzzy logic. The user interface was designed according to computer-based interactive systems methodology (ISO 9241-210:2010).

In phase 5 **(test of the decision support system)**, the implemented prototype was tested, refined, and validated with the aid of an experimental study using a laboratory use case. The Learning Factory 4.0 of the "Production Planning Lab" of the University of Applied Sciences Emden/Leer was used as a test environment for the experimental study (Zarte et al., 2019e). For this approach, the production processes of the learning factory were represented in a digital twin using the simulation software AnyLogic®. The concept of the decision support system was tested and proven through a sensitivity analysis and Monte Carlo simulation experiments to answer RQ 3.

In phase 6 **(evaluation of the research results)**, the research results were conceptually validated. For this approach, qualitative criteria were selected and adapted according to the purpose of this research. Then, the research results were validated based on the qualitative criteria by determining whether the model's theory and assumptions are reasonable. Based on the evaluation results, problems, needs, and challenges were identified for production planning, considering sustainability aspects.

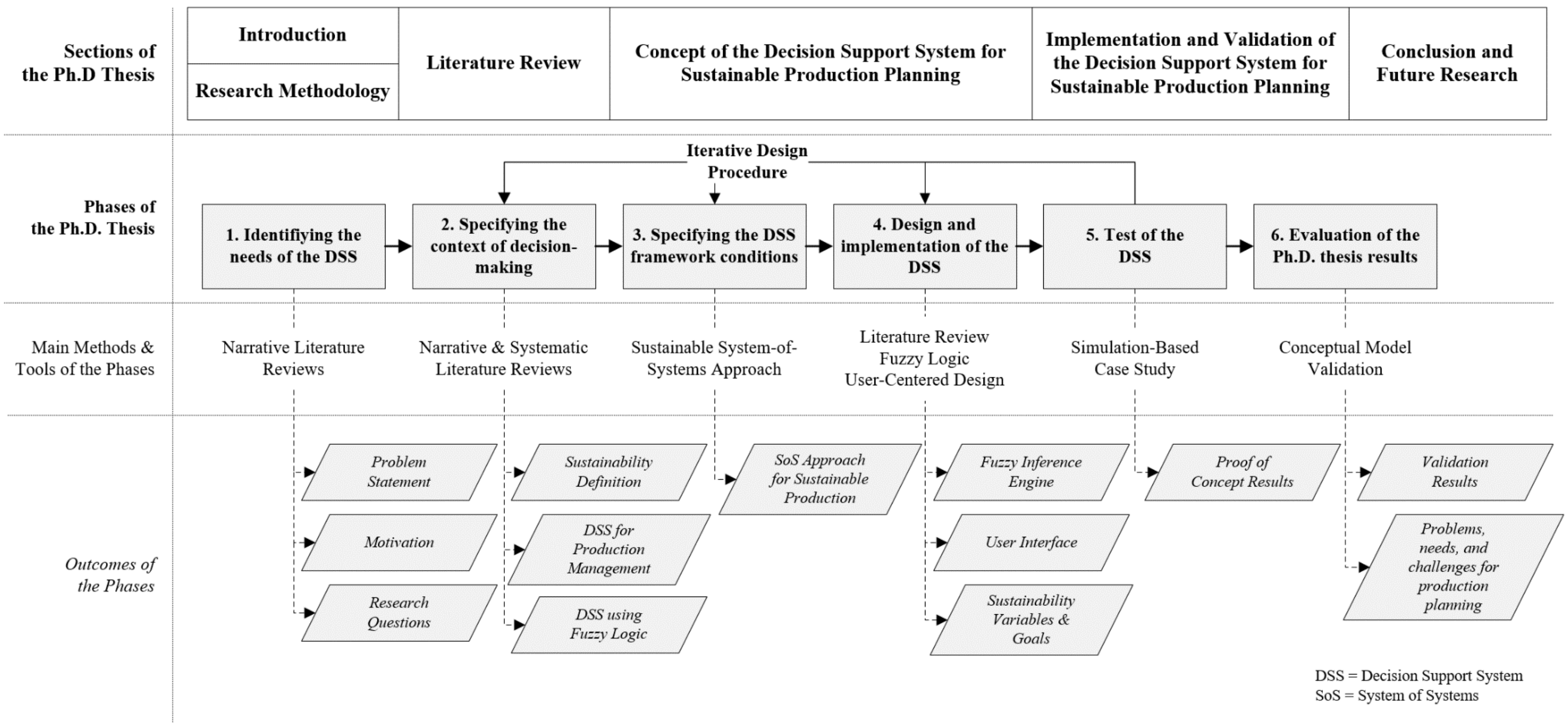


Figure 2.1: Research methodology for the study.

3

LITERATURE REVIEW

In general, a **narrative literature review** aims to identify relevant studies that describe a problem of interest. However, these reviews have no specific RQ or systematic methodology (Booth et al., 2016). In contrast, a **systematic literature review** aims to give a comprehensive overview of studies that describe a problem following specific RQs. Figure 3.1 presents a systematic literature review methodology to search, analyze, and synthesize the studies.

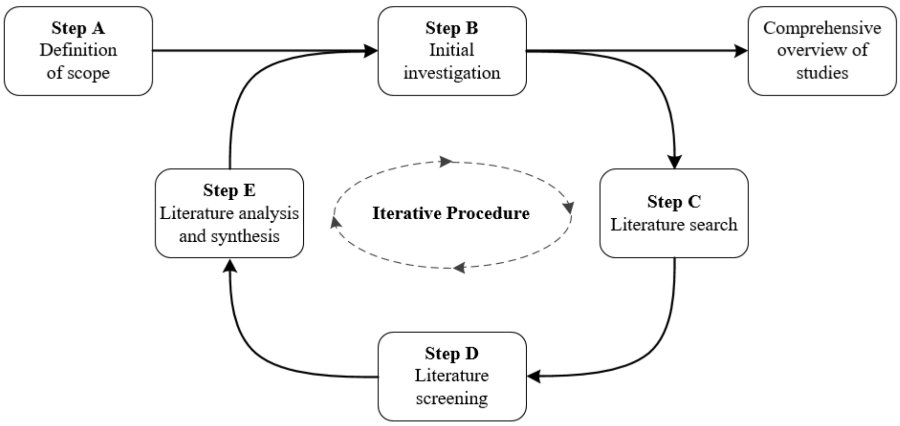


Figure 3.1: Systematic literature review methodology adapted from vom Broke et al. (2009).

The basis for a systematic literature review is a definition of its scope (step A). The scope contains the research goal and questions. In step B, an initial investigation of relevant studies was made to determine literature search criteria (e.g., keywords, databases) and limitations (e.g., timeframe, journals) based on the scope. With the aid of these criteria and limitations, studies were searched in common scientific databases (e.g., Web of Science, ScienceDirect, Scopus) in step C. The found studies were screened in two steps (step D). First, the found studies were pre-analyzed by viewing the title, keywords, and abstract. Second, the pre-analyzed studies were analyzed in a full-text review. Finally, the selected studies were synthesized following the literature review goal and answering the RQ in step E.

With these narrative and systematic literature review procedures, the theoretical background and state of the art for this research are presented. First, Section 3.1 presents general and widely accepted definitions to explain the terms sustainability, sustainable manufacturing, and sustainability-based production planning. Based on these explanations, Section 3.2 presents the results of a systematic literature review considering decision support systems for sustainability-based production management. Afterward, literature review results are presented while considering sustainability-based production management using fuzzy logic (Section 3.3).

3.1 Definitions and Concepts for Sustainability

In general, no standard definition exists for sustainability, sustainable manufacturing, and sustainability-based production planning. Therefore, researchers always need to define what they mean by sustainability in relation to their presented research contributions. A narrative review has been performed for this approach to present widely accepted definitions, concepts, and frameworks for sustainability that are relevant for this research.

3.1.1 Sustainability and Sustainable Development

The term sustainability has been discussed in the last 300 years. In 1713, von Carlowitz recognized an increasing lack of wood for the mining industry and suggested new sustainable forest management methods. The author introduced the basic principle that the resource extraction rate must be lower or equal to the resource regeneration rate (von Carlowitz, 1713). For 200 years, this principle for sustainable resource extraction was only applied in a few industry sectors, such as the forest and fishing industries (Jörissen et al., 1999).

In the early 1970s, sustainable resource management again came into the focus of researchers, governments, and enterprises. The study "Limit of Growths" discussed the lack of global resources. The author investigated three global scenarios considering the impacts of the growing human population, industrialization, resource extraction, pollution, and food production. Two of the scenarios end in the collapse of the global system by 2050, while a third scenario resulted in a stabilized global system. This was the first time that unsustainable development was recognized as a global problem by researchers, governments, and enterprises, and this recognition led to many sustainability discussions (Meadows, 1974).

The main results of these discussions were reported in the study "Our Common Future" from the World Commission on Environment and Development (WCED), which provides widely accepted definitions, guidelines, and sustainable development principles. The study proposed the following still widely accepted definition for sustainable development (WCED, 1987): “development which meets the needs of current generations without compromising the ability of future generations to meet their own needs.” The report remains the basis for past and current political conferences and strategies on sustainable development, such as “Agenda 21” (United Nations, 1992) and “Sustainable Development Goals” (United Nations, 2015b).

In 1997, Elkington proposed another widely accepted concept for sustainability. The TBL concept has been adapted in several studies and defines sustainability according to three essential dimensions (see Figure 3.2): economic, social, and environmental. New technologies, processes, business models, or products must be balanced with all three dimensions to be sustainable. The TBL concept represents a qualitative concept only and gives no guidelines or procedures for sustainable assessment according to the three dimensions (Elkington, 1997).

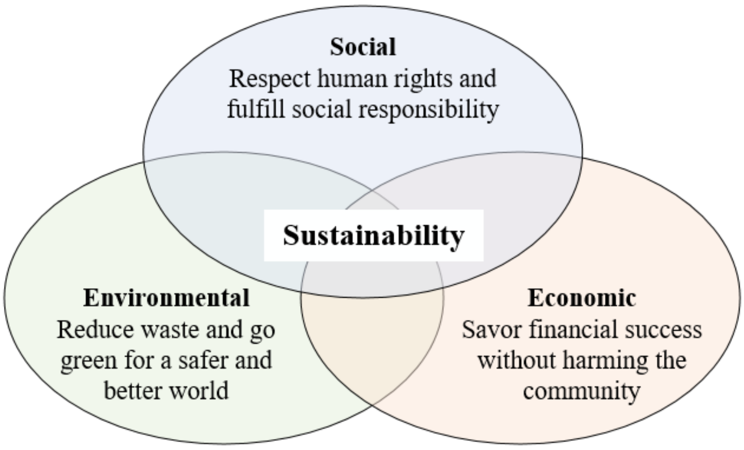


Figure 3.2: TBL concept proposed by Elkington (1997).

However, driven by financial markets’ expectations, most enterprises still consider the economic dimension more important than the other two. Moreover, enterprises started to compensate for deficits in the social or environmental aspects through benefits in the economic dimension (Hauschild et al., 2017). This phenomenon is also known as the “rebound effect.” The “rebound effect” occurs when resource- or energy-efficiency improvements through, for instance, technological progress are overestimated regarding their potential to mitigate environmental and social impacts. Reasons for this could be ignoring the behavioral responses from the market or other stakeholders (Binswanger, 2001). For example, car fuel-efficiency improvements lead to cheaper driving and less greenhouse gas (GHG) emissions. However, the same fuel-efficiency improvements also result in users driving more, buying bigger cars, or spending their cost savings on other products (Font Vivanco et al., 2016). Therefore, resource- or energy-efficiency technologies are not automatically leading to sustainable development.

A new understanding was required for the TBL concept. Rockström et al. (2009) suggested a nested perspective on sustainability instead of the fragmented concept (see Figure 3.3). The nested perspective shows the environmental dimension as a basis for the other two sustainability dimensions. Social and economic sustainability can only be achieved if the environmental dimension is fully secured (Rockström et al., 2009).

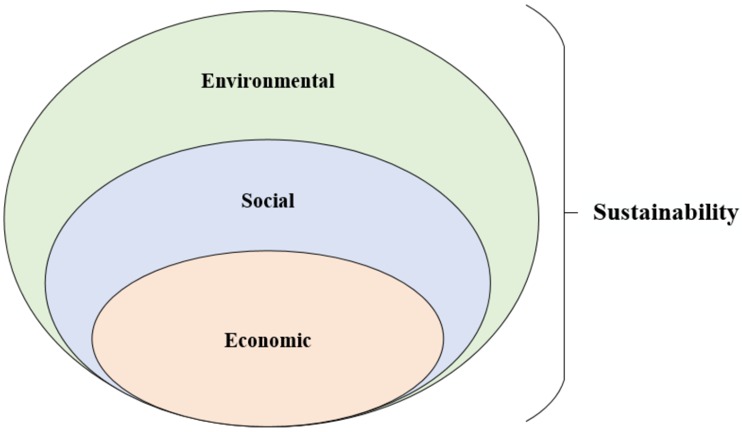


Figure 3.3: Nested TBL concept proposed by Rockström et al. (2009)

The nested perspective on the TBL is focused on environmental sustainability and assumes that the other two aspects (social and economic) cannot exist without the environment. However, the social dimension in the form of ergonomics should be an integral part of finding solutions to the current global environmental and economic challenges (Siemieniuch et al., 2015; Thatcher et al., 2018). Therefore, Thatcher and Yeow (2016) proposed a sustainable SoS approach (Thatcher and Yeow, 2016). This approach consists of three components (see Figure 3.4): (1) a nested hierarchy of systems, (2) timeframes for systems to be sustainable, and (3) sustainability goals.

First, a **nested hierarchy** is used to describe the sustainable SoS approach. In general, a system is generally understood as "an assemblage of components that produces behavior or function not possible from any component individually. An SoS is an emergent class of systems built from components which are large-scale systems in their own right" (Maier, 1998). Wilson (2014) recommended describing an SoS as a relationship between a target and related systems. A target system can interact with numerous sibling systems, parent systems, and child systems (Wilson, 2014). For example, the enterprise system (target system):

- contains several departments (child systems),
- competes with other enterprise systems (sibling systems), and
- interacts with the local and global environment (parent systems).

Second, the **timeframe** of a system to be sustainable needs to be considered. Costanza and Patten (1995) noted that no system is infinitely sustainable in its current form, not even the universe. In fact, it is the very nature of systems to be dynamic, having a natural lifetime, after which it will become unable to cope with changes (Costanza and Patten, 1995).

Third, an SoS approach cannot be considered sustainable unless it considers multiple **sustainability goals**. Thatcher and Yeow use the TBL to categorize these sustainability goals but give no specific examples.

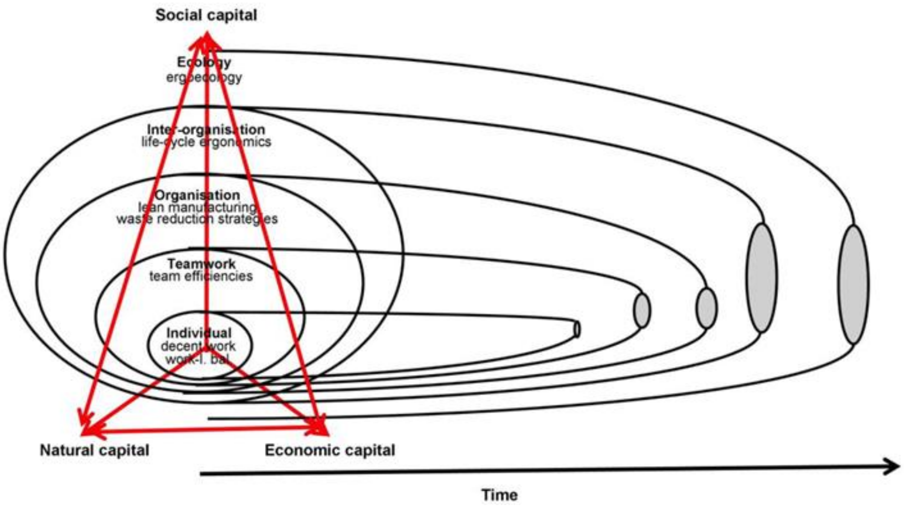


Figure 3.4: Sustainable SoS approach proposed by Thatcher (2016).

However, several widely used goal and indicator frameworks exist that consider the sustainability of the global system. Based on the nested perspective on the TBL, Rockström (2015) proposed the planetary boundary concept, which quantifies 11 indicators to secure the environmental dimension (see Figure 3.5). The planetary boundaries give a quantitative guideline to prevent human activities from causing unacceptable environmental changes in the global system (Rockström, 2015).

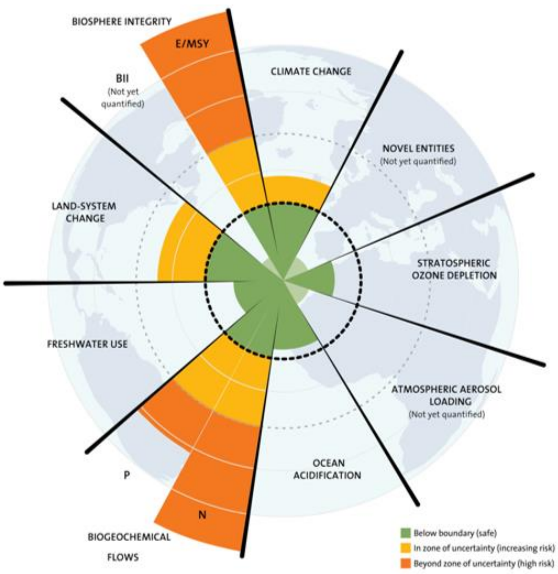


Figure 3.5: Planetary boundaries approach (Steffen et al., 2015)

The planetary boundary concept focuses on environmental sustainability, arguing that the other two dimensions (social and economic) cannot exist without an environmentt. The UN developed the SDGs, which considers the social dimension too (see Figure 3.6). The SDGs are a collection of 17 goals intended to be achieved by 2030. Each goal has eight to 12 targets, and each target has between one to four indicators to measure its progress (United Nations, 2015b).

Figure 3.6: The Sustainable Development Goals (United Nations, 2015b).

The presented selection of definitions for sustainable development and sustainability shows an evolution of these terms from first their principles to global goals for more sustainability. However, a more detailed discussion of the definitions and concepts is out of scope for this research, and this section gives a basic understanding of sustainability only.

3.1.2 Sustainable Manufacturing

The world has passed through three industrial revolutions. In the ongoing fourth industrial revolution (industry 4.0), new concepts to fully interconnect the physical and the digital manufacturing worlds, thus improving the overall performance of manufacturing systems, are being implemented in production systems (Thangaraj and Lakshmi Narayanan, 2018). Industry 4.0 enables knowledge-based decision-making among production management and optimization processes according to sustainability aspects (Stock and Seliger, 2016). These different definitions, concepts, and perspectives on industry, sustainability, and sustainable development lead to the question of in which conditions a manufacturing system can be sustainable.

Moldavska and Welo analyzed existing definitions for sustainable manufacturing and discussed the understanding of what researchers mean by the concept (Moldavska and Welo, 2017). The analysis revealed that the most commonly used definition is that proposed by the U.S. Environmental Protection Agency (EPA): “the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources. Sustainable manufacturing also enhances employee, community, and product safety" (USEPA, 2017). However, Moldavska and Welo determined that 86% of the identified definitions are used in less than three articles, which shows a wide deviation from existing sustainable manufacturing definitions (Moldavska and Welo, 2017).

For example, Zhang and Haapala proposed a similar definition to the U.S. EPA's and which is close to the perspective of sustainable development as an integrated relationship: "Sustainable manufacturing can be defined as producing products in a way that minimizes environmental impacts and takes social responsibility for employees, the community, and consumers throughout a product's life cycle, while achieving economic benefits" (Zhang and Haapala, 2015). According to this definition, sustainable manufacturing can only be achieved when environmental impacts are minimized, social requirements are considered, and economic benefits are generated along the product's life cycle.

However, the author gave no information about how many environmental impacts must be minimized or which social requirements must be considered to achieve sustainable manufacturing. In contrast, Bonvoisin et al. defined sustainable manufacturing as "the creation of discrete manufactured products that, in fulfilling their functionality over their entire life cycle, cause a manageable amount of impacts on the environment (nature and society) while delivering economic and societal value" (Bonvoisin et al., 2017). This definition is more focused on the product's impacts and asserts that they must be manageable.

Existing definitions lack detailed information about possible sustainability impacts caused by the manufacturing system on other systems. For this approach, several categorization frameworks exist for sustainable manufacturing (Zarte et al., 2019c). For this research, the categorization framework provided by the American National Institute of Standards and Technology (NIST) has been adapted. NIST developed a framework that classifies sustainability measures into a multi-level categorization framework according to the TBL (Joung et al., 2013). The categorization framework provides a reasonable and well-organized structure that companies and institutes can use to assess the sustainability of their products, processes, and research approaches related to manufacturing. Several other researchers have already used the categorization framework to structure sustainability impacts (Ocampo et al., 2016; Song and Moon, 2017). Figure 3.7 presents the adapted categorization framework for sustainability impacts used in this research. The figure is also structured according to the TBL and contains examples to show which sustainability measures can be allocated to a specific category.

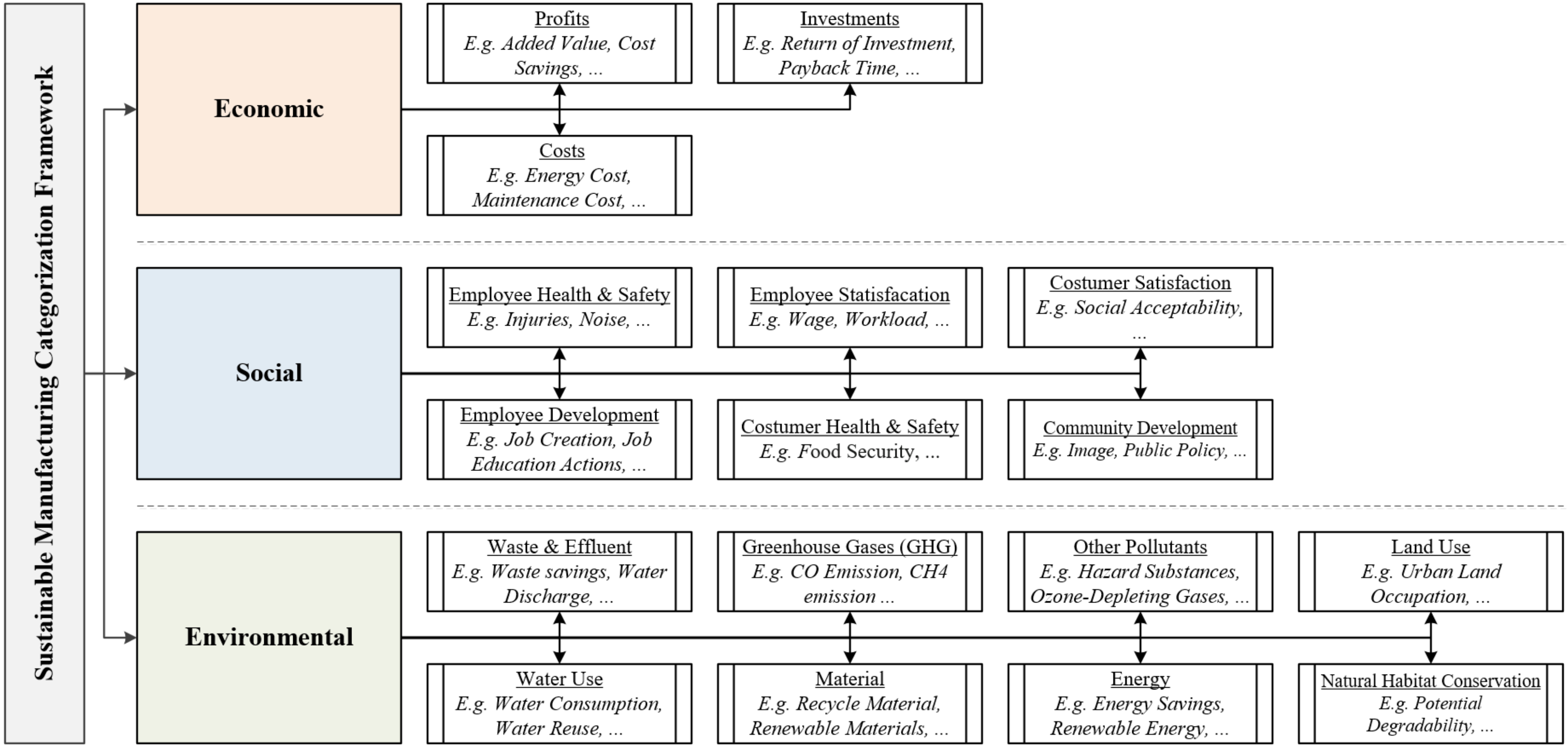


Figure 3.7: Sustainability variable framework adapted from Joung et al. (2013).

3.1.3 Sustainability-Based Production Planning

As mentioned before, sustainable development is widely defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987). This definition of "sustainable development" has become very common; however, its implications for designing or improving an existing system, especially manufacturing systems, remains quite vague. Generically, to develop a system means, first, to assess the actual improvement potential of the current context compared to an envisaged better state and, second, to identify alternative lines of action to reach this better state and implement the ones which are acceptable, viable, and feasible (Daly, 1990). Moreover, the flexibility of systems plays an essential role and must be considered, too, in responding to potential events or context changes affecting the system's intended performed (REFA, 1990).

From a manufacturing perspective, production planning tools are used to determine and optimize the future states of manufacturing systems according to actual framework conditions (e.g., available resources), planning goals (e.g., specific production output), and production system flexibilities. Production flexibility indicates the production system's ability to adapt to changing framework conditions and considered planning goals. It can be expressed by the opportunity to, for instance, handle different materials, change production sequences, or shift production tasks (REFA, 1990). Production planning is already well described in standards and literature for production management. It is defined as a decision-making process to schedule the timely acquisition, utilization, and allocation of production resources (machines, labor, and production inputs) to specific production activities in the short term (DKE, 2013). Conventional production planning aims to reach a manufacturing state that satisfies customer requirements in the most efficient way regarding product quantity and quality (DKE, 2013; Graves, 1999). Figure 3.8 presents relevant flows as an input-output (IO) model for conventional production planning. The figure considers the input materials, labor, costs, and output products for a general production system. The input and output can be normalized to relevant information for production planning, e.g., production tasks, orders, and time (dash arrow in Figure 3.8).

Due to crises (e.g., climate crisis, extinction of species, shortage of natural resources, and health crises (Bundesregierung, 2019)), the customer requirements for conventionally produced products have shifted to more sustainably produced products that avoid environmental and social impacts (WBCSD, 2008). Therefore, the goal of production planning needs to be extended by an environmental and social perspective (Giret et al., 2015; Sutherland et al., 2016).

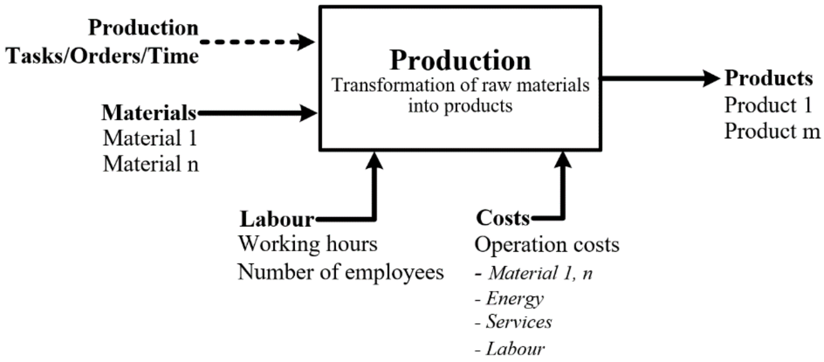


Figure 3.8: IO model for production planning (Zarte et al., 2019c).

For this approach, several definitions exist to describe a sustainable state of manufacturing systems that needs to be reached with production planning tools (Moldavska and Welo, 2017). For example, the U.S. EPA proposed the following widely used definition for sustainable manufacturing: "the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources. Sustainable manufacturing also enhances employee, community and product safety." This definition gives a general view on sustainable manufacturing only. Therefore, Figure 3.9 presents additional IO flows relevant for sustainability-based production planning. The figure presents sustainability aspects as an integrated relationship between economic, social, and environmental aspects. Moreover, the sustainability aspects are organized according to the main categories from the NIST framework (see previous section): water, energy, material, waste, labor, costs, emissions, effluent, and waste.

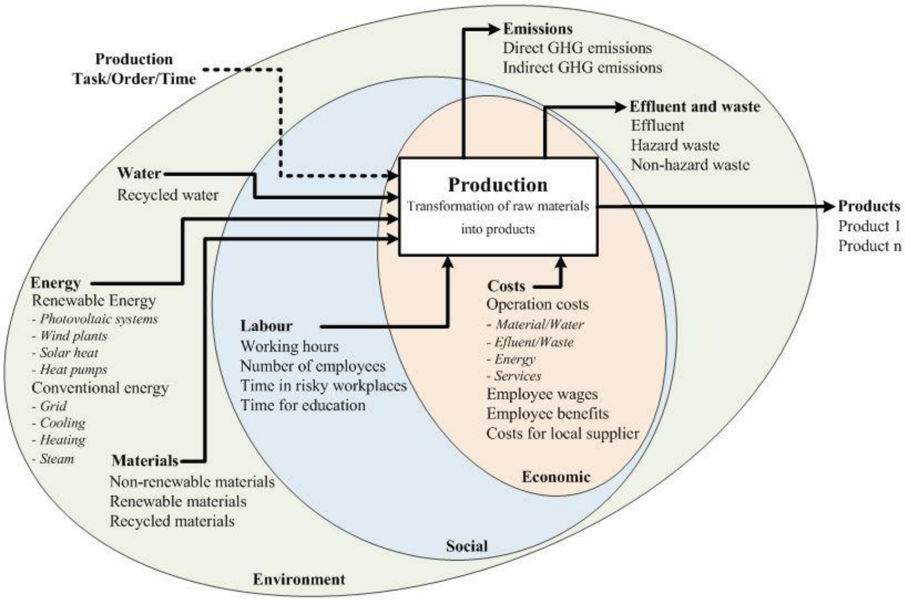


Figure 3.9: IO model for sustainability-based production planning (Zarte et al., 2019c)

However, conventional production planning is already complex, as many factors contribute to planning processes, such as complex production systems, changing product portfolios, unpredictable events, and machine breakdown. Addressing sustainability objectives, such as limits for emissions and resources and the health status of employees in manufacturing operations scheduling, in addition to classical production objectives for quantity and quality, makes production scheduling much more complex (Akbar and Irohara, 2018; Giret et al., 2015).

However, a definition for sustainability-based production planning is derived from these commonly accepted and used definitions of sustainable development, sustainable manufacturing, and production planning. This research defines sustainability-based production planning as

"the planning of production activities to achieve conventional (economic) production goals, ensuring the enterprises´ operation. Moreover, additional sustainability goals must be achieved, avoiding, reducing, or compensating environmental damages and social issues."

3.2 Decision Support Systems for Sustainability-Based Production Management

In general, decision support systems are information systems that help decision-makers in operational, tactical, and strategic management activities. For this approach, relevant data, information, and knowledge are collected, prepared, and evaluated by the decision support system (Turban et al., 2005). Several literature reviews exist that consider decision support systems for different purposes surrounding sustainability-based production management processes (Biel and Glock, 2016; Diaz-Balteiro et al., 2017; Giret et al., 2015; Jamwal et al., 2021).

The systematic literature review Zarte et al. (2019a) aimed to identify commonly used decision support system methods and variables for sustainability-based production management. For this approach, the literature review is focused on research approaches, which consider all sustainability dimensions (economic, environmental, and social), and on decision support systems applied in production management activities along the product life cycle. The original published literature review analyzed studies until the publication date of June 2017. For this research, the literature review results were updated using the same search criteria and limitations until the publication date of October 2021.

For the systematic literature review, an initial literature review was made to determine suitable search criteria and limitations for the literature review goal. Table 3.1 presents the used keywords for the literature review.

Table 3.1: List of keywords for the literature search.

Group 1	Group 2
Multi-criteria	Sustainable
Decision-making	Sustainability
Decision support	---
Production planning	---

The keywords were categorized into two groups: keywords for decision support systems (group 1) and keywords for sustainability (group 2). Literature searches were done in the b-on database using the keywords. For the search, one keyword from group 1 was combined with one keyword from group 2. This means that, in total, eight combinations were used to search the literature in the database. For the searches, the following limitations were applied:

- The 300 most relevant papers were revised for the possible keyword combinations;
- Only the literature in the databases mentioned was considered;
- Only peer-reviewed journal papers published in English were considered; and
- The considered timeframe was from 2007 to 2021.

With these limitations, the relevant literature has been searched and selected. The following criteria were defined for the literature selection:

- Only decision support systems for sustainable manufacturing focusing on industrial production processes and products were considered;
- The decision support systems must meet all three sustainability dimensions (economic, environmental, and social);
- The decision support system must be allocatable to one of the following product and production life-cycle phases:
    - product and production design,
    - production planning,
    - production, or
    - remanufacturing of processes and products;
- Decision support systems for the energy industry and agriculture were not considered;
- Decision support systems for households, urban areas, industrial parks, and countries were not considered; and
- Decision support systems for the selection of suppliers were not considered.

Based on these criteria, the found research articles were evaluated in two steps. First, the found papers were pre-analyzed by viewing the title, keywords, and abstract. Through this pre-analysis, 198 relevant papers were identified. Figure 3.10 presents the number of papers found in the pre-analysis step by publication year.

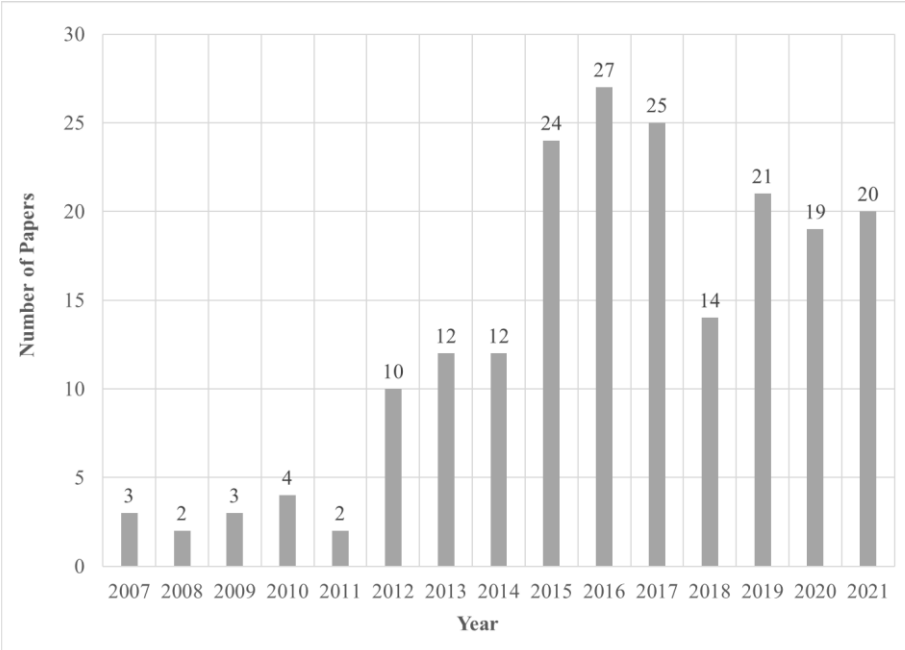


Figure 3.10: Number of papers published in the timeframe 01.01.2007–11.30..2021.

Second, the relevant papers were analyzed in a full-text review. Through this review, 26 papers were identified that met all defined criteria for the literature selection. The relevant literature was discussed and categorized by life-cycle phases, methods, and sustainability variables.

Figure 3.11 shows the ratio of studies found for production management activities along the product life cycle: product and production design, production planning, production, and remanufacturing of processes and products. For the strategic-related management activities (product and production design and remanufacturing of products and processes), 69% of the studies were identified, while the operational-related management activities (production planning and production evaluation) comprised the remaining 31%. Only a few studies considered all three sustainability dimensions, particularly for production planning. This finding was acknowledged in the literature review presented by Giret et al. (2015) too. The review results show that decision support systems' developments are more focused on the strategic planning level, which is not reflected well at the operational level, where decision-making is driven mainly by the sustainable dimensions: environment and economics. In addition to economic and environmental objectives, production planning systems should also consider social planning objectives (Giret et al., 2015; Grosse et al., 2017; Sutherland et al., 2016).

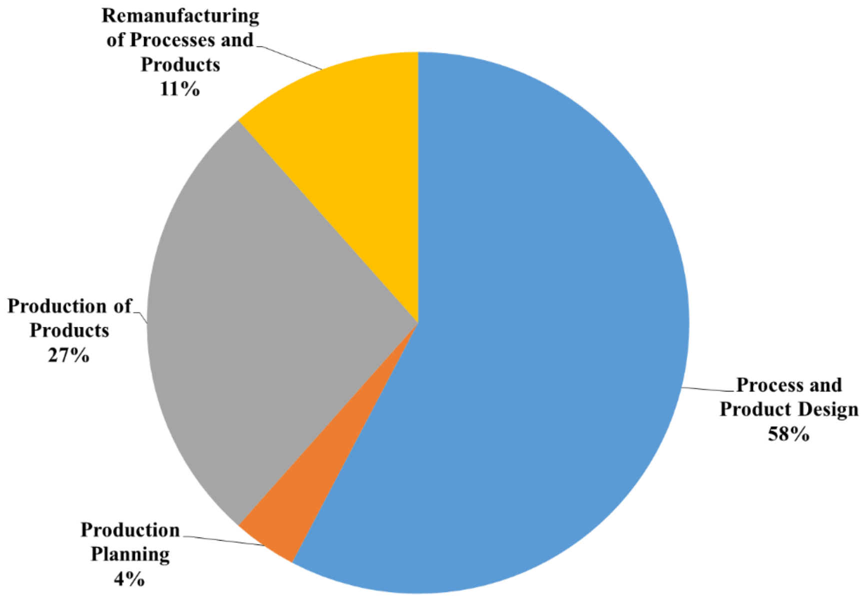


Figure 3.11: Ratio of studies found for life-cycle phases.

In order to answer the RQs for this literature review, the found decision support systems were analyzed considering the used decision-making methods and variables. First, a suitable decision-making method needed to be selected to address a sustainability problem in the context of production systems. Table 3.2 presents the literature review results for the decision-making methods identified relating to strategic, tactical, and operational production management activities: product and production design (1), production planning (2), production (3), and remanufacturing of processes and products (4).

Table 3.2: Decision-making methods identified for the life-cycle phase.

	Design (1)	**Planning (2)**	**Production (3)**	**Remanufacturing (4)**	**Total**
Analytic Hierarchy Process (AHP) / Analytic Network Process (ANP)	9	0	5	0	14
Fuzzy Logic	3	0	6	2	**11**
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	1	0	1	1	**3**
Elimination Et Choix Traduisant la Realité (ELECTRE)	1	0	0	1	**2**
Weighted Sum Model (WSM)	2	0	0	0	**2**
Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)	2	0	0	0	**2**
Sustainability Balanced Scorecard (SBSC)	0	0	1	0	**1**

Table 3.2: Decision-making methods identified for the life-cycle phase (continued).

	Design (1)	Planning (2)	Production (3)	Remanufacturing (4)	Total
Complex Proportional Assessment of Alternatives (COPRAS)	0	0	1	0	**1**
Interpretive Structural Modeling (ISM)	0	0	1	0	**1**
Nondominated Sorting Genetic Algorithm (NSGA)	0	0	0	1	**1**
Grey Relational Analysis (GRA)	1	0	0	0	**1**
Decision-Making Trial and Evaluation Laboratory (DEMANTEL)	1	0	0	0	**1**
Monte Carlo Simulation	1	0	0	0	**1**
Preference Set-Based Design (PSD)	1	0	0	0	**1**
Total	**21**	**0**	**11**	**4**	

In contrast to the literature review for multicriteria analysis from Herva and Roca (2013), analytic hierarchy and network processes (AHP/ANP) were found as the most-used decision-making approach for sustainability-based production management. This result is consistent with the literature review finding for multicriteria methods done by Diaz-Balteiro et al. (2017). It seems that the combination of the method AHP/ANP with another technique to weigh and evaluate the sustainability variables (e.g., fuzzy logic) is a commonly used method for solving sustainability decision problems. However, no decision-making method was found for production planning that simultaneously evaluates economic, environmental, and social aspects. The found production planning approaches were limited to a single sustainability aspect, a conclusion also reached in the literature review for sustainability in operation scheduling conducted by Giret et al. (2015).

Moreover, the literature review results show no trend relating to specific decision-making methods and production management activity. A reason for this result could be that the selection of decision-making methods follows no generally accepted procedure, and the reasons for selecting a decision-making method are often unclear. However, another reason could be that the categorization of the decision-making methods is too generic. A more detailed categorization of the decision-making methods is required, e.g., enterprises' branch, specific sustainability problems, and type of production or product.

Second, relevant sustainability goals and variables need to be selected for sustainability-based production management. The selection of specific sustainability variables for decision support systems has been analyzed in this review through a categorization framework (see

Section 3.1.2). Figure 3.12 shows that sustainability variables are often used for decision support systems relating to strategic, tactical, and operational production management.

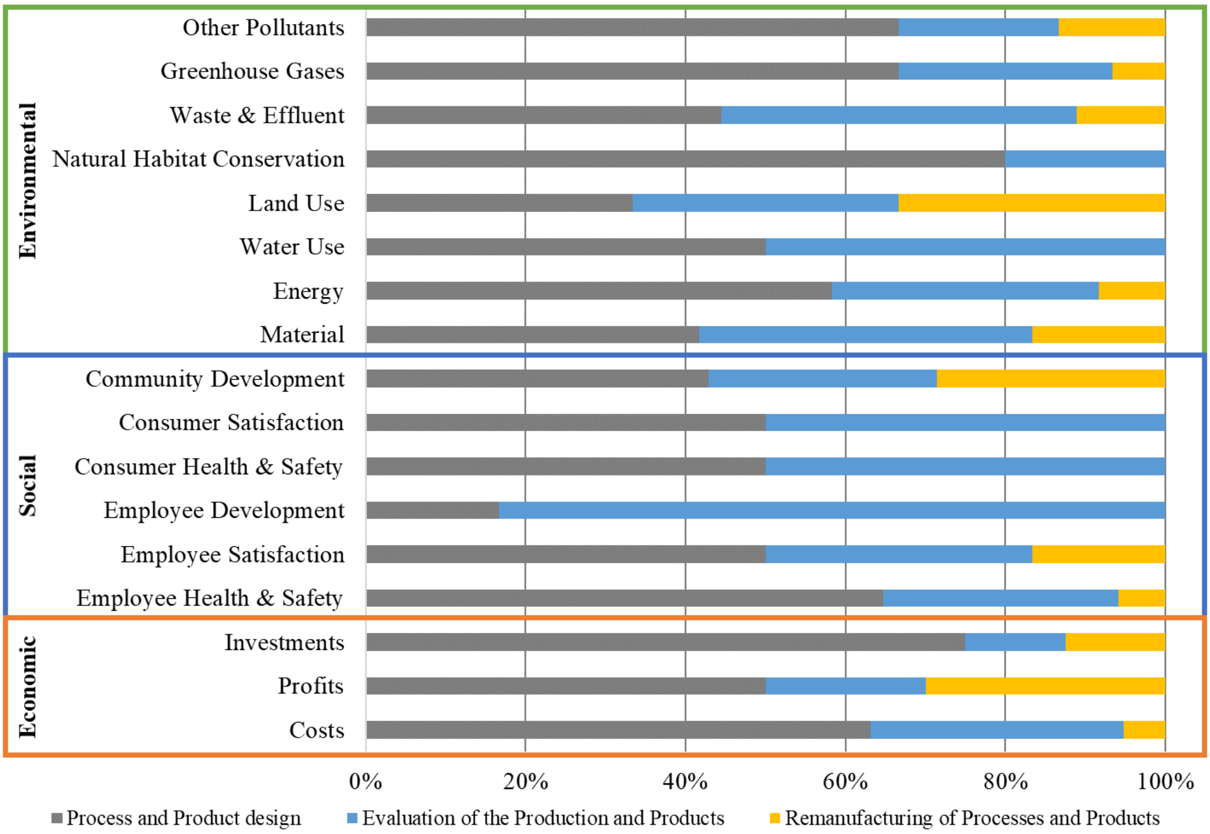


Figure 3.12: Ratio of used sustainable variables in relation to the life-cycle phase.

For the design of production and products, the economic dimension of sustainability is focused on variables for production costs. For the social dimension, most of the studies considered variables related to the health and safety of employees. The analysis for the environmental dimension shows a trend toward analyzing the energy consumption and resulting emissions of GHGs and other pollutants. An evaluation of the sustainability variables for production planning systems was not possible because no studies were found. The evaluation of sustainability variables for production and product evaluation shows similar results compared to the management activity design of production and products. The studies considering remanufacturing were also limited, but all studies considered variables for the profits of remanufacturing alternatives. For the social and environmental dimensions, no trend could be observed.

However, the selection of variables follows no commonly accepted procedure, being selected subjectively by the researchers based on no objective rules. Therefore, the published decision-making results can hardly be considered for similar decision-making problems. Thus, common criteria and selection procedures for methods and variables are required (e.g., the sustainable variable framework proposed by NIST (Joung et al., 2013)) for the sustainable evaluation of manufacturing processes to objectively evaluate sustainability aspects and to make decision-making results more transparent and comparable. Standard procedures and methods for the sustainable evaluation would also help avoid the "greenwashing" of products and production processes by enterprises through the consideration of, for instance, an incomplete overview of sustainability aspects (Yu et al., 2020). Moreover, Inoue et al. (2012) recognized that the evaluation of social variables is an issue for decision-makers because of missing data and/or insufficient data quality. Another issue is the weighting of sustainability variables. Most of the weighting methods are based on subjective viewpoints from experts. Zhang and Haapala (2015) suggested decision-makers should carefully select and analyse the weights on each sustainable variable, and sensitivity analyses should be used to verify the decision results.

Finally, additional literature reviews are required for this research to identify applicable sustainability variables for production planning processes, which can be used to improve production programs according to sustainability aspects. These reviews are part of the proposed decision support system concept and are presented in Section 4.2.

3.3 Sustainability-Based Production Management Using Fuzzy Logic

In general, mathematical models require input and output measurements to validate a model's performance (Bungartz et al., 2009). The sustainability assessment of systems lack output data because sustainability cannot be directly determined or measured (Al-Sharrah et al., 2010; Phillis and Kouikoglou, 2009). Therefore, fuzzy logic is one opportunity to overcome this problem and has been used as the decision-making method in this research. Therefore, a new literature review was conducted accounting for the theoretical background of fuzzy logic and existing fuzzy logic approaches for sustainability-based production management.

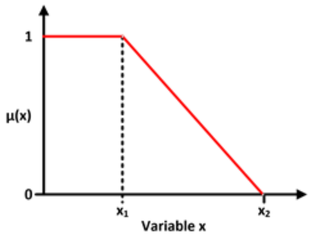
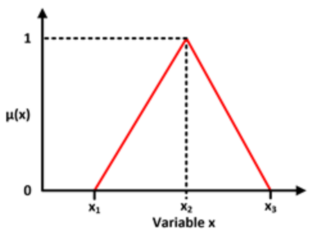
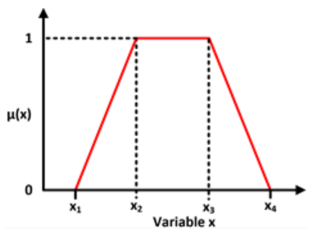
3.3.1 Fuzzy Logic

Zadeh (1965) developed fuzzy logic in response to the inherent uncertainty and complexity involved in real-world modeling problems. Fuzzy logic provides appropriate mathematical tools to assess the state of systems using expert knowledge, which can be represented in various ways, such as mathematical functions, linguistic rules or expressions, or numerical values. Moreover, quantitative and qualitative variables can be normalized to evaluate systems using soft thresholds. A fuzzy inference model (FIM) consists of the following three key steps (Cornelissen et al., 2001):

1. **Fuzzification** converts selected variables (x) into fuzzy values (μ_x) in intervals between zero and one using fuzzy sets;
2. **An inference model** combines the fuzzy values to a single fuzzy value using fuzzy operators; and
3. **Defuzzification** converts the aggregated fuzzy value into a crisp value representing the fuzzy model's output.

In the first step of the fuzzy model, the fuzzification process transforms crisp values of the variables (x) into a unitless fuzzy value (μ_x) with the aid of fuzzy sets. A fuzzy set is used to interpret a selected variable, e.g., sustainability is low, medium, or high. A fuzzy set is mathematically formulated, and each element of the variable is mapped to a value between zero and one using a membership function (Zadeh, 1965). Table 3.3 gives an overview of three typical linear membership functions that can be used for different purposes. The x-axis in the graphical presentation represents the selected variable (x), whereas the y-axis represents the fuzzy value (μ_x) in an interval between zero and one. Similar membership functions are expressed by polynomial or exponential functions. These functions were not considered in this research.

Table 3.3: Overview of common membership functions for the fuzzification process.

Membership Function Shape	Graphical Presentation	General Mathematical Formulation
Z-shape		$\mu_{(x)} \begin{cases} 0, & x \geq x_2 \\ \dfrac{x_2 - x}{x_2 - x_1}, & x_1 < x < x_2 \\ 1, & x \leq x_1 \end{cases}$
Triangle		$\mu_{(x)} \begin{cases} 0, & x \leq x_1 \\ \dfrac{x - x_1}{x_2 - x_1}, & x_1 < x \leq x_2 \\ \dfrac{x_2 - x}{x_2 - x_3}, & x_2 < x < x_3 \\ 0, & x \geq x_3 \end{cases}$
Trapezoidal		$\mu_{(x)} \begin{cases} 0, & x \leq x_1 \\ \dfrac{x - x_1}{x_2 - x_1}, & x_1 < x \leq x_2 \\ 1, & x_2 \leq x \leq x_3 \\ \dfrac{x_4 - x}{x_4 - x_3}, & x_3 < x < x_4 \\ 0, & x \geq x_4 \end{cases}$

In the second step of the fuzzy model, multiple fuzzy values μ_x are combined. In general, the inference process combines fuzzy values using rules and fuzzy operators (Zadeh, 1965). For this approach, two typical fuzzy rule inference engine types have been considered in this research (Becker and Börcsök, 2000):

1. The **individual rule inference model** contains individual rules for a single variable and defined fuzzy sets. The number of rules rises exponentially with the number of selected variables and defined fuzzy sets.
2. The **composition rule inference model** contains aggregated fuzzy set rules represented as a function for a single variable. Therefore, the number of rules is equal to the number of variables.

Individual rule inference models are widely used for machine control automatization problems (fuzzy control) because the rules can be set for non-linear process parameters independently. However, the complexity of individual rule inference models increases with the number of selected variables and defined fuzzy sets. Composition rule inference models are recommended in case of a changing number of variables for the fuzzy inference model (Becker and Börcsök, 2000). Both types of inference models require fuzzy operators to combine multiple fuzzy inputs. In general, three types of fuzzy operators exist for the inference process (Becker and Börcsök, 2000):

- intersection operators (t-Norm),
- union operators (s-Norm), and
- average operators.

Additionally, the fuzzy operator can be parametric or non-parametric, and multiple fuzzy operators can be combined to form a customized fuzzy operator function. Table 3.4 presents an overview of common non-parametric fuzzy operators.

Table 3.4: Overview of common non-parametric fuzzy operators.

	Operator Name	Mathematical Expression
Intersection Operator (t-Norm)	Minimum	$\mu_{A\cap B} = Min(\mu_A, \mu_B)$
	Hamacher Product	$\mu_{AhB} = \frac{\mu_A * \mu_B}{\mu_A + \mu_B - \mu_A * \mu_B}$
	Algebraic Product	$\mu_{A*B} = \mu_A * \mu_B$
	Einstein Product	$\mu_{AeB} = \frac{\mu_A * \mu_B}{2 - (\mu_A + \mu_B - \mu_A * \mu_B)}$

Table 3.4: Overview of common non-parametric fuzzy operators (continued).

Union Operator (s-Norm)	Maximum	$\mu_{A\cup B} = Max(\mu_A, \mu_B)$
	Hamacher Sum	$\mu_{Ah'B} = \frac{\mu_A + \mu_B - 2 * \mu_A * \mu_B}{1 - \mu_A * \mu_B}$
	Algebraic Sum	$\mu_{A+B} = \mu_A + \mu_B - \mu_A * \mu_B$
	Einstein Sum	$\mu_{Ae'B} = \frac{\mu_A + \mu_B}{1 - \mu_A * \mu_B}$
Average Operator	Arithmetic Average	$MA_{\bar{\mu}} = \frac{1}{n} * (\mu_A + \mu_B + \cdots + \mu_n)$
	Geometric Average	$MG_{\bar{\mu}} = \sqrt[n]{\mu_A * \mu_B * \ldots * \mu_n}$
	Root Mean Square	$RMS_{\bar{\mu}} = \sqrt{\frac{1}{n} * (\mu_A * \mu_B * \ldots * \mu_n)}$

The fuzzy operators have different effects on the model outcome (Becker and Börcsök, 2000). Figure 3.13 presents the effects of the union, average, and intersection operator on the fuzzy model outcome for the fuzzy input values $\mu_A = 0.2$ and $\mu_B \in [0,1]$. **Union operators** have a linguistically reinforcing effect, and inference results correspond to the highest fuzzy value or higher ($\mu_{A\cup B}$). Lower fuzzy values have no or small impacts on the inference result. **Average operator** results range between the highest and lowest fuzzy values ($MA_{\bar{\mu}}$). The linguistic effect depends on the average operator´s nature. For example, the geometric average has a degrading effect, while the root means square has a reinforcing effect compared to the operator arithmetic average results. **Intersection operators** have a linguistically degrading effect, and inference results correspond to the lowest fuzzy value or smaller ($\mu_{A\cap B}$). Higher fuzzy values have no or small impacts on the aggregation result. However, the fuzzy operator is crucial in interpreting the inference results and needs to be selected carefully by experts according to their decision-making goals.

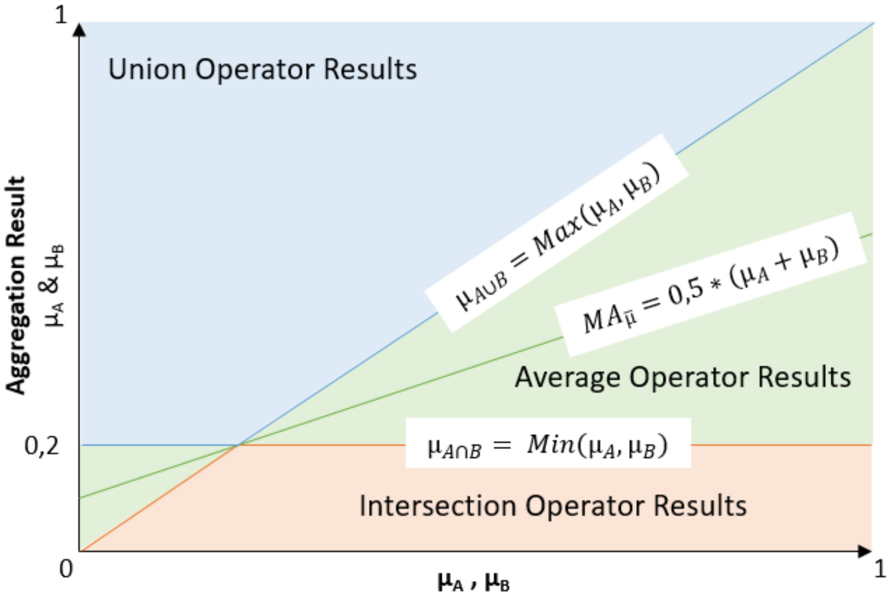


Figure 3.13: Exemplary effects of the fuzzy operators on the model outcome.

In the third step of the fuzzy model, the combined fuzzy values are defuzzified. In general, the defuzzification process converts a fuzzy value back to a crisp value (z*). For this approach, several methods exist (Ross, 2010), e.g., centroid methods, average methods, and max membership methods. Table 3.5 summarizes six common defuzzification methods and presents their graphical presentation and mathematical expressions. The defuzzification function is crucial in interpreting the fuzzy inference model results and needs to be selected carefully by experts according to their decision-making goals.

Table 3.5: Overview of common functions for the defuzzification process.

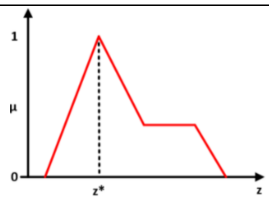
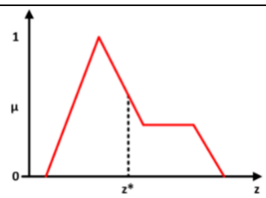
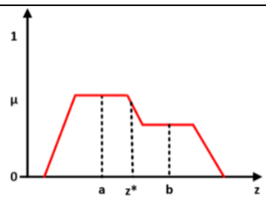
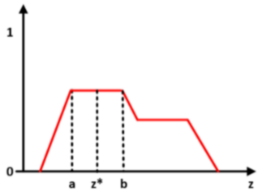
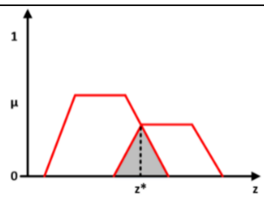
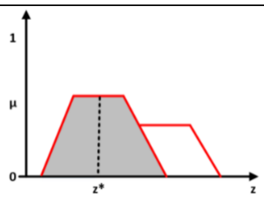
Defuzzification Method	Graphical Presentation	Mathematical Expressions
Max membership principle		$\mu_{z*} \geq \mu_z, \quad for\ all\ z\ \in Z$
Centroid method		$z^* = \frac{\int \mu_z * z * dz}{\int \mu_z * dz}$
Weighted average		$z^* = \frac{\sum \mu_{\bar{z}} * \bar{z}}{\sum \mu_{\bar{z}} * \bar{z}}$

Table 3.5: Overview of common functions for the defuzzification process (continued).

Defuzzification Method	Graphical Presentation	Mathematical Expressions
Mean max membership		$z^* = \frac{a+b}{2}$
Center of sums		$z^* = \frac{\sum_{k=1}^{n} \mu_z * \int \bar{z} * dz}{\sum_{k=1}^{n} \mu_z * \int dz}$
Center of the largest area		$z^* = \frac{\int \mu_z * z * dz}{\int \mu_z * dz}$

3.3.2 Fuzzy Inference Models for Sustainability-Based Production Management

Section 3.2 presents a systematic literature review considering decision support systems for sustainability-based production management. Based on this literature review, the following systematic literature review is focused on decision support systems, which specifically use FIM to evaluate enterprise systems according to sustainability aspects. The literature review aimed to analyze and understand how existing FIMs are designed for different decision-making problems. Table 3.6 presents the systematic literature review's search settings and selection criteria. 11 papers were identified for the full-text analysis based on the search settings.

Table 3.7 presents the literature review results, showing characteristics from the found fuzzy decision models applied to sustainable manufacturing. The characteristics contain information about the model goal, target system, variables for the fuzzification process, inference model, and defuzzification process.

The literature review results suggest that fuzzy logic is one opportunity in the decision-making processes for product and process design and strategic enterprise planning when it comes to considering sustainability aspects. These models consider, for example, various design uncertainties (Inoue et al., 2012), process alternatives, and product alternatives (Ghadimi et al., 2012; Hemdi et al., 2013; Kucukvar et al., 2014). Moreover, several studies support the strategic decision-making of the enterprises using different sustainability variable frameworks, e.g., the Global Reporting Initiative (GRI) (Pislaru et al., 2019), ISO 26000 (Calabrese et al., 2019), and individual frameworks (Elysia and Nugeraha Utama, 2018, 2010; Rajak and Vinodh, 2015).

Table 3.6: Search settings for systematic literature review for Fuzzy Logic.

Criteria/Limitation	**Search Setting**
Keywords	Fuzzy logic, sustainable manufacturing
Database	b-on
Timeframe	January 2011 – December 2020
Type of Research	Journal articles, book chapters, conference articles
Language	English
Selection Criteria	- Focused on inference engines that use fuzzy logic or fuzzy logic in combination with another decision-making method. - The decision support systems must have met all three sustainability dimensions (economic, environmental, and social) - Other target systems, such as countries, households, and supply chains, were not considered

However, existing FIMs for decision support for sustainability-based production management cannot be directly adapted for operative production planning, which is the focus of this thesis. These models consider variables that are not applicable for operative planning. The developed fuzzy models analyze variables considering the ergonomic design of workplaces and the design of renewable energy plants, which affect the production system in the long term. For operative sustainability-based production planning, the model must consider variables that analyze the production system in a short time (e.g., the day-to-day schedule), such as daily accumulated physical stress on the worker and daily renewable energy availability. Moreover, the found inference engines only apply to specific products and processes. Operative production planning needs flexible and generic inference engines that can be easily adapted for different production situations producing different amounts and kinds of products (Kreimeier, 2012). Another problem is that existing approaches for sustainability-based production planning consider single sustainability aspects only (Giret et al., 2015). A decision-making process needs to be developed that is applicable independently of the variable's nature to assess the state of sustainability.

Table 3.7: Fuzzy decision-making models applied to sustainable manufacturing.

Reference	Goal of the Model	Target System	Input Variables (Membership Function)	Inference model	Defuzzification
(Calabrese et al., 2019)	Ranking of relevant sustainability issues for strategic decision-making	Enterprise	- Seven core subjects of ISO 26000 (Triangular)	- Analytic hierarchy process	Centroid defuzzification
(Pislaru et al., 2019)	Corporate sustainability evaluation of an enterprise	Enterprise	- Seven environmental indicators (Trapezoidal) - Three economic indicators (Trapezoidal)	- If-then rules - MIN-MAX operator	Centroid defuzzification
(Calabrese et al., 2016)	Ranking of GRI indicators for sustainability reporting	Enterprise	- GRI indicators	- Analytic hierarchy process	---
(Rajak and Vinodh, 2015)	Social performance of an enterprise	Enterprise	- 60 social indicators (Triangular)	- Weighted arithmetic averaging operator	Average score
(Kouikoglou and Phillis, 2011)	Corporate sustainability evaluation of an enterprise	Enterprise	- 18 indicators (Triangular)	- If-then rules - MIN-MAX operator	Height method
(Piluso et al., 2010)	Sustainable evaluation of a chemical plant	Enterprise	- 11 IChemE indicators (Triangular)	- If-then rules - MIN-MAX operator	Score
(Hendiani et al., 2020)	Analyzing the status of sustainable development in manufacturing	Production	- Basic indicators for the evaluation of the TBL (Trapezoidal)	- Weighted arithmetic averaging operator	Average score
(Bitter et al., 2016)	Sustainability evaluation of renewable energy plants	Production	- Basic indicators for the evaluation of the TBL (Triangular)	- If-then rules - Algebraic product aggregation	Singleton defuzzification
(Hemdi et al., 2013)	Sustainable electrical power generation	Production	- Set of environmental, social, and economic indicators (Triangular)	- If-then rules	Centroid defuzzification
(Rajabalipour Cheshmehgaz et al., 2012)	Production planning of an assembly line	Production	- Cycle time (Z-shape) - Overall physical workload (Z-shape) - Accumulated risk of postures (Non-Fuzzy Goal)	- Weighted functional operator	Genetic algorithm to maximize aggregated value
(Kucukvar et al., 2014)	Ranking of pavement options	Products	- 16 sustainability environmental and social indicators	- Weighted geometric averaging operator - Weighted arithmetic averaging operator	---
(Ghadimi et al., 2012)	Sustainability-based product design	Product	- Set of environmental, social, and economic indicators (Triangular)	- If-then rules	Weighted score

4

CONCEPT OF THE DECISION SUPPORT SYSTEM

A detailed description of the general concept of the decision support system for sustainability-based production planning is presented in this section. The section aims to give a detailed description of the design and functions of the developed decision support system components.

The structure of the sub-sections is as follows. Section 4.1 introduces a general scope for the decision support system. The scope is presented as an SoS approach for sustainability-based production planning, which discusses the affected systems and related sustainability aspects. Based on the general scope, Section 4.2 presents an overview of applicable variables for sustainability-based production planning that can be applied in the decision support system. Based on the scope and list of relevant variables, the mathematical formulation of the FIM is presented for sustainability-based production planning in Section 4.3. Section 4.4 presents a user interface design example to show the results of the FIM to the user.

4.1 System of Systems Approach for Sustainability-Based Production Planning

The definition of the scope is an essential element of sustainability assessment procedures. For example, the life-cycle assessment standard (DIN EN 14040:2009-11, 2009) defines the following items for the scope: description of the considered system, including the definition of the system boundaries, the functions of the system, functional unit, data requirements, and assumptions and limitations. This research used the sustainable SoS approach (see Section 3.1.1) to define the scope for sustainability-based production planning. The approach integrated the current hierarchal conceptualization of possible system interactions with important concepts from the sustainability literature, including the TBL approach and the notion of time horizons for sustainability.

Zarte et al. (2020b) adapted the sustainable SoS approach for sustainability-based production planning. Figure 4.1 presents a nested hierarchy of the systems for sustainability-based production planning, including stakeholders for sustainable manufacturing (owner, employee, customer, supplier, local community, and global community) and product life-cycle phases (material acquisition, production, use, recycling, and disposal). The following subsection explains the SoS approach in more detail.

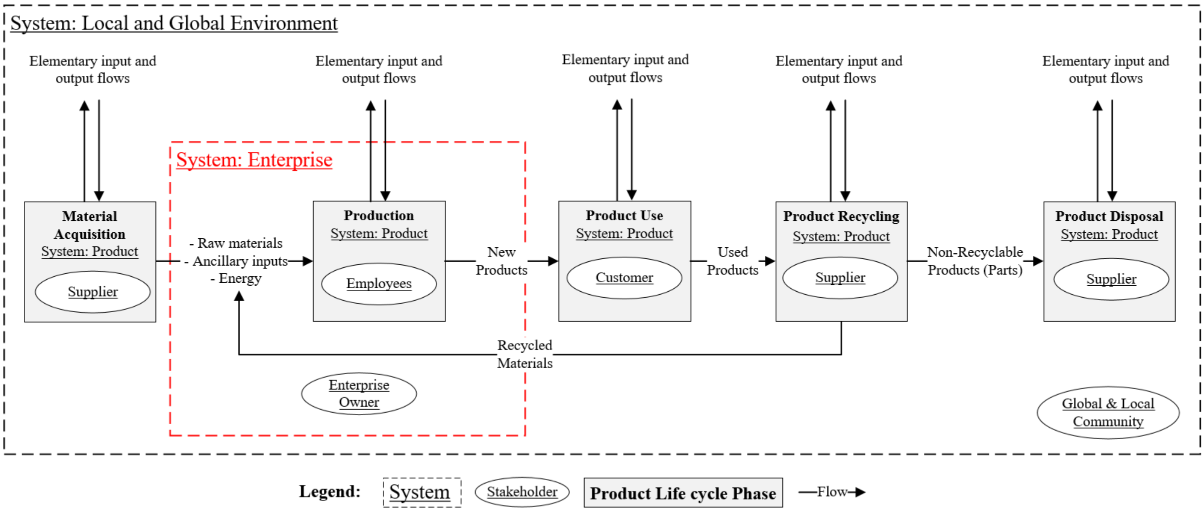


Figure 4.1: SoS approach for sustainability-based production planning (Zarte et al., 2020b).

4.1.1 Nested System Hierarchy

The presented nested hierarchy for sustainability-based production planning consists of four systems that interact with one another:

- Global environment,
- Local environment,
- Enterprise, and
- Product.

The presented hierarchy is universal and not complete. For example, the enterprise system can be divided into a production system, single production machines, or cells. Moreover, multiple suppliers or costumers can be considered for providing or buying materials and products. These systems need to be defined individually for specific cases but neglected in this general SoS approach for sustainability-based production planning. However, the general scope for sustainability-based production planning can be explained without the missing systems.

In general, the scope definition requires identifying a target system, which then is used to determine sustainability impacts between the target system and other systems. As the target system, the enterprise system is defined for sustainability-based production planning (see the red rectangle in Figure 4.1). The local and global environmental systems are considered parent systems. The physical border between the enterprise and local environment can be clearly defined in terms of the land use by the enterprise. The physical border between the local and global environments is fluid and must always be defined for each enterprise. The size of the enterprise, its type, and the marketplaces for its products are important factors defining the global system. The local and global communities can include human populations, cooperating organizations, and competing enterprises.

The product cannot clearly be defined as a sibling, child, or parent system. A product passes through several life-cycle phases and affects different systems´ sustainability. Moreover, the impact of the effects depends on the product and is described as elementary IO flows. The elementary flows include the use of elementary resources and releases to air, water, and land associated with the life-cycle phase. The elementary input flows considered include, for example, relevant climate information for renewable energy generation (such as radiation, wind speed, moisture, and air pressure), water, air, and fossil fuels (natural gas, oil). The elementary output flows considered include emissions in the form of sewage, waste, and GHGs.

In the "material acquisition" life-cycle phase, external suppliers collect and generate materials, energy, and ancillary inputs, which are provided to the enterprise system. The collection and generation processes affect the sustainability of local and global systems; the extent of such effects depends on the geographical relationship of these systems to the enterprise systems. The "production" life-cycle phase involves the enterprise system and transforms materials into products. The production of products directly affects the sustainability of the enterprise system and is what this researched focused on. In the "product use" life-cycle phase, customers use the products provided by the enterprise system. After the use time, the "product recycling" life-cycle phase provides recycled materials to the production and is usually performed by external suppliers. Non-recyclable products are disposed of in the "product disposal" life-cycle phase, affecting local and global environmental systems.

4.1.2 Timeframe

The sustainable SoS model considers the time over which a system should be sustainable. The time is dependent on its relative position in the parent-sibling-child nested hierarchy. An organization is expected to have a longer natural lifespan than its component systems (Thatcher, 2016). Therefore, products included in the enterprise system have a shorter time span to be sustainable than products related to the local and global environment systems. It is assumed that the enterprise system can react faster to changing requirements for sustainability than local and global systems. For example, a car producer can change its product portfolio for new car versions relatively quickly (one to three years) in comparison to customers buying new cars (five to ten years). However, determining the time dimension to be sustainable for products is a challenging task and depends on several factors, such as the lifetime of a product, political restrictions or support, the needs and interests of customers, and environmental and social impacts of other systems.

4.1.3 Sustainability Goals

The goals for sustainability-based production planning from a human perspective are defined according to the stakeholders' interests. These interests have been identified and discussed by Zarte et al. (2018a). Table 4.1 gives a brief overview of the results.

Table 4.1: Overview of stakeholders in sustainable manufacturing and their main interests.

Stakeholder	Description of the stakeholder	Description of the general interest
Enterprise Owner	Individual with a financial investment in the business who is responsible for the strategic orientation of the enterprise (target system).	Interested in the economic value creation of the company.
Employee	Individual who provides their skills to a firm, usually in exchange for a monetary wage.	Interested in safe and healthy workplaces, opportunities for training and qualification activities, and fair salaries.
Customer	Can be viewed as an end-user of a product, service, or process.	Interested in consuming products to satisfy their needs.
Supplier	Provides goods or services to the company.	Interested in economic value creation.
Local Community	A spatially related group of individuals using a shared resource base within which a company enterprise exists.	Interested in a healthy and safe living environment.
Global Community	A community outside the boundaries of the local community (e.g., a state, national, or international entity)	Interested in a healthy and safe world.

The stakeholders are related to specific life-cycle phases and systems (see Figure 4.1). Goals and related variables must follow current restrictions for sustainable manufacturing and the stakeholders' interests. Through a text review, specific SDGs have been applied for the sustainable SoS approach (United Nations, 2015b). Moreover, the NIST sustainability variable framework (see Section 3.1.2) was reviewed to allocate possible variables for sustainability-based production planning. The analysis results are presented as a root-cause diagram (see Figure 4.2).

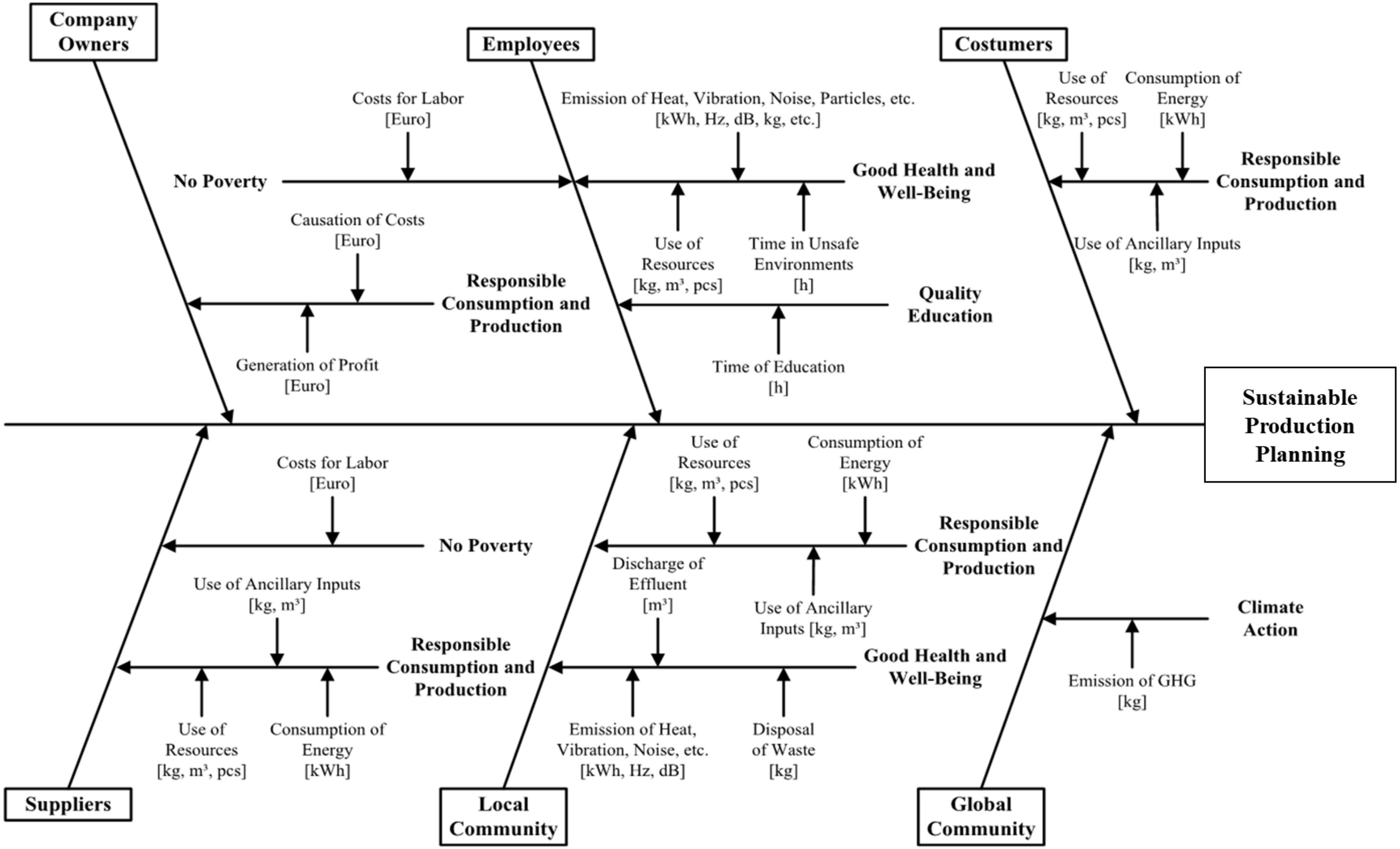


Figure 4.2: Root-cause diagram presenting stakeholder-related sustainability goals.

For the analysis, a set of criteria was defined to determine sustainability goals and variables for production planning:

- The goal and related variables must have a predictable quantitative impact on short- and mid-term production planning;
- The goal and related variables must be relevant regarding sustainable manufacturing and to the sustainability goal;
- The goal and related variables must be understandable and easy to interpret by the company; and
- the goal and related variables must be allocable to one (or more) stakeholder groups supporting their interests.

Depending on the needs and interests of the stakeholders, the identified goals have different meanings and implications to the stakeholders, meaning they require different variables to control the goals. For example, the sustainable goal "responsible consumption and production" is allocated to multiple stakeholder groups: owners, customers, suppliers, and the local community. Local communities are interested in protecting local resources, and the sustainable variables are focused on the local resources available for manufacturing companies. However, few customers are interested in products produced using renewable and recycled materials, green energy, and environmentally compatible ancillary inputs. The sustainable variable "use of resources" was thus selected for both stakeholder groups but with a different focus on the type of resources controlled.

4.2 Variables for Sustainability-Based Production Planning

The formulation of the FIM required a selection of suitable variables for sustainability-based production planning. Section 4.1 already gives an overview of sustainability-based production planning goals and variables. The considered SDGs (see Figure 4.2) give a comprehensive sustainability framework but no information about the relevance for operational production planning, so further research was required (Zarte et al., 2018a). For this approach, a systematic literature review was conducted to identify the relevance of the variables for sustainability-based production planning from production and ergonomic perspectives (Zarte et al., 2019c, 2019d).

The selection of suitable variables is an individual process that depends on the goal for sustainability-based production planning (see Section 3.1.3) and the model scope (see Section 4.1). As mentioned before, sustainability-based production planning aims to achieve conventional (economic) production goals, ensuring the enterprises´ operational success. Moreover, additional sustainability goals must be achieved, avoiding, reducing, or compensating for environmental damages and social issues.

Based on this main goal, Figure 4.3 presents the general framework of sub-goals and variable categories for sustainability-based production planning. The framework consists of two main categories of goals and variables required for the decision support system. First, the decision support system considers one or multiple conventional production planning goals. These goals must be fully achieved (f = 1) to secure the production's operation. Second, the FIM determines the potential to improve a production program according to sustainability goals. The improvement potential is determined using an FIM, which expresses production programs' sustainability as a number between one (μ_P = 1: high potential to improve sustainability) and zero (μ_P = 0: low potential to improve sustainability).

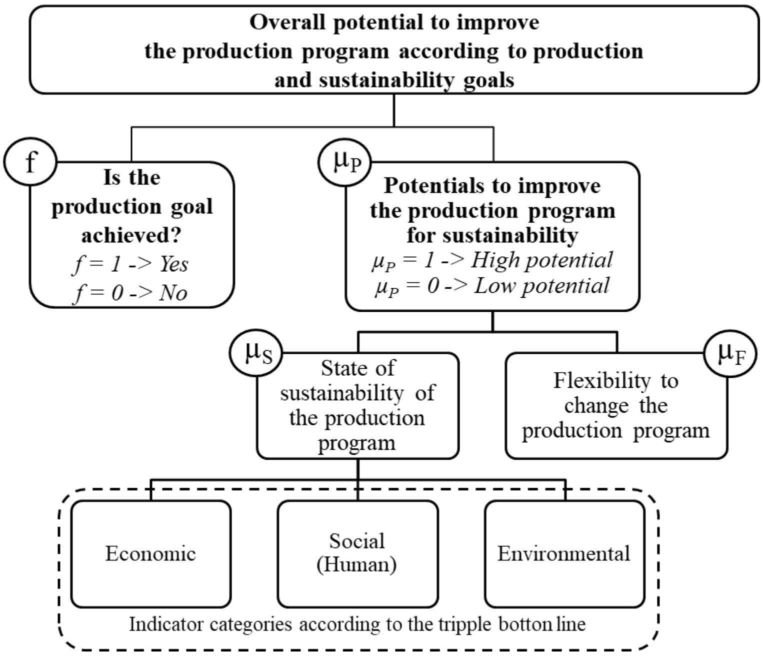


Figure 4.3: Goal and variable framework for sustainability-based production planning.

The improvement potential is determined by multiple sets of goals and variables consisting of two groups targeting the:

1. State of sustainability (μ_S) considering economic, environmental, and social aspects of the production system; and
2. Flexibility (μ_F) to implement a defined change of sustainability state in a production system through, for example, shifting the start of production activities, interrupting production activities, using alternative resources for activities, or adjusting the process parameter.

Based on these categories, a systematic literature review was performed to create a general list of goals and variables that have already been used for sustainability-based production planning. The goals and variables were categorized according to conventional planning aspects, sustainability aspects (economic, environmental and social), and production flexibility aspects. Moreover, the relevance of the variables was determined by considering the frequency of the found variables in the literature.

The literature results identify recently published systematic literature reviews (2015–2019) for sustainability-based production planning (see Table 4.2). These reviews considered sustainability-based production planning from a fragmented perspective, neglecting at least one sustainability aspect. Moreover, the environmental sustainability aspect is often focused on single environmental problem fields (waste, energy).

Table 4.2: Overview of literature reviews for sustainability-based production planning.

Reference	Number of Reviewed Papers	Economic Sustainability	Environmental Sustainability	Social Sustainability
(Giret et al., 2015)	45	X	X	
(Le Hesran et al., 2019)	70	X	X (Focus on Waste Reduction)	
(Biel and Glock, 2016)	89	X	X (Focus on Energy Efficiency)	
(Trost et al., 2019)	18	X		X
(Grosse et al., 2017)	25	X		X

The presented literature reviews have been analyzed to find relevant articles. For this approach, first, the reviewed articles were extracted from the literature reviews and analyzed to identify similarities. The results are presented in Figure 4.4. The figure presents the total number of papers as a bubble chart and shared papers as arrows between the bubbles. The literature review by Giret has the most total shared papers with other literature reviews. Moreover, Trost used several articles for social production planning, which can also be found in reviews for environmental production planning. In contrast, Grosse used papers for social production planning that were shared with Trost only.

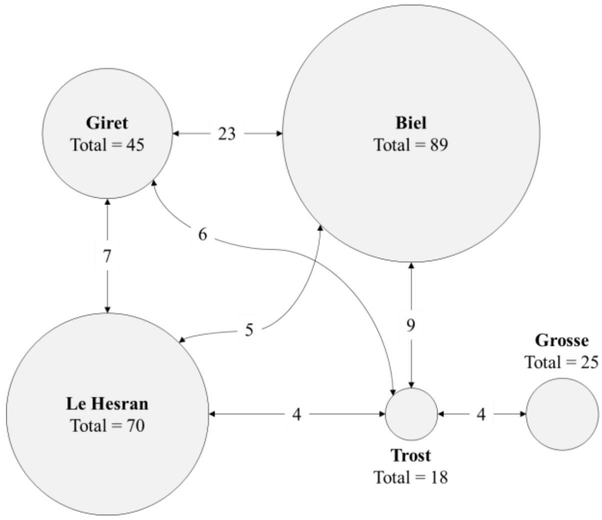


Figure 4.4: Total and shared papers of the analyzed literature reviews.

165 single papers were identified for this literature review. The following criteria were applied to identify relevant studies:

- The publication date must be after 2000;
- The publication must be available in the usual databases (e.g., Science Direct, Scopus);
- The study must have considered at least one sustainability aspect of machine scheduling for the manufacturing industry sector. Studies that considered only conventional production planning goals (e.g., makespan reduction) were not considered;
- Approaches considering product- or machine-related planning problems (e.g., cutting-stock, single-machine energy efficiency) were not considered.

According to these selection criteria, 62 relevant articles were identified to develop a comprehensive list of sustainability-based production planning goals and variables considering economic, environmental, and social sustainability.

Table 4.3 presents the literature review results for classical production goals and variables. In 41 studies, five unique conventional planning goals and variables were identified and combined with other sustainability goals and variables. These goals and variables aimed to make a product in a minimal time (51%), set a threshold for the production volume (17%), or consider the minimization of the total inventory (2%). However, most studies centered on the makespan and tardiness time variable for decision-making in sustainability-based production planning.

Table 4.3: Goals and variables for conventional production planning.

Production Planning Goal (Unit)	Variable	Ratio in Found Studies (n = 41)
Minimal total makespan to finish jobs (h)	Makespan	51%
Processing of jobs within a certain makespan (h)	Makespan	22%
Minimal total tardiness time of jobs (h)	Tardiness time	17%
Threshold for production volume (%)	Production volume	7%
Minimal total inventory of products and semi-products (number of products/semi-products)	Inventory of products and semi-products	2%

Table 4.4 presents the literature review results of goals and suitable variables for economic-sustainability production planning. In 12 studies, four unique economic planning goals and variables were identified and combined with other conventional and sustainability goals and variables. Half of the articles aimed to reduce the total production costs (50%). The other studies considered specific production cost aspects, such as energy costs (33%) and disassembly and shredding costs (8%). However, the list neglects other typical production cost aspects, e.g., personal costs. These aspects are usually indirectly considered evaluating, for instance, the required workforce.

Table 4.4: Goals and variables for economic sustainability.

Production Planning Goal (Unit)	Variable	Ratio in Found Studies (n = 12)
Minimal total production costs (Euro)	Production costs	50%
Minimal energy production costs (Euro)	Energy cost	33%
Minimal disassembly and shredding costs for recycling purposes (Euro)	Disassembly and shredding costs	8%
Minimal cost-weighted processing quality instability index (Euro)	Cost-weighted processing quality instability index	8%

Table 4.5 presents the literature review results of goals and suitable variables for environmental-sustainability production planning. In 43 studies, six unique environmental planning goals and variables were identified and combined with other conventional and sustainability goals and variables. Most articles considered goals and variables for energy consumption (30%) and freshwater use (21%). However, it was not valuable to integrate all presented environmental sustainability goals and variables in a single model. The variables needed to be independent of one another, avoiding double-counting sustainability benefits and impacts. For example, a reduction of the total energy consumption also reduces GHG emissions. Therefore, an additional goal for GHG emissions made no sense if the GHG was related to energy consumption only.

Table 4.5: Goals and variables for environmental sustainability.

Production Planning Goal (Unit)	Variable	Ratio in Found Studies (n = 43)
Minimal total energy consumption (kWh)	Energy consumption	30%
Minimal use of freshwater through reusing (m^3)	Use of freshwater	21%
Minimal carbon dioxide (equivalents) emission (tons CO_2)	Carbon dioxide (equivalents) emission	19%
Minimal total non-processing energy (kWh)	Non-processing energy	12%
Threshold for the peak power (kW)	Peak power	12%
Minimal number of setups of machines to avoid the emission of waste, effluent, and GHGs (number of setups)	Number of setups	7%

Table 4.6 presents the literature review results of goals and suitable variables for social-sustainability production planning. In 15 studies, five unique social planning goals and variables were identified and combined with other conventional and sustainability goals and variables. Most of the articles considered the health and wellbeing of employees (56%). However, the small number of found articles (three times lower than environmental sustainability) shows that social sustainability production planning has been limited within the literature. Therefore, the list of goals and variables for social-sustainability production planning is likely incomplete.

Table 4.6: Goals and variables for social sustainability.

Production Planning Goal (Unit)	Variable	Ratio in Found Studies (n = 15)
Minimal risk of injuries and/or health impacts caused by physical stress on employees (risk of injuries, (human) energy expenditure performing jobs, occupational risk assessment (OCRA) index)	Risk of injuries caused by ergonomic stress on employees; (human) energy expenditure performing jobs	56%
High learning rate of employees processing jobs (number of processed jobs)	Learning rate of employees	19%
Low forgetting rates of employees processing jobs (time without processing the job)	Forgetting rates of employees	13%
Threshold for the minimum required human workforce for job tasks (h)	Human workforce	6%
Maximal skill level of the employee	Skill level of the employee	6%

Table 4.7 presents the literature review results for variables considering production flexibility that have been considered to improve production systems' sustainability. In general, production flexibility indicates the production system's ability to adapt to planning goals (REFA, 1990). However, flexibility variables can be divided into partial flexibilities to describe a production system's flexibility more accurately (Marks et al., 2018). These partial flexibilities

can be used for production planning to improve sustainability aspects. Moreover, production flexibility depends on the production process type (job shop, batch, or flow production). Job shop production systems offer the highest flexibility, while flow production systems offer the lowest (Chapman, 2006).

Table 4.7: Goals and variables for production flexibility (Marks et al., 2018).

Partial Flexibility	Variable
Machine flexibility describes the convertibility of machines to new products/materials.	Setup time
Material-handling flexibility describes the (re-)routability and storage ability of materials.	Queue time in buffer zones
Volume flexibility describes the capacity adaptability of production resources.	Production capacity
Process flexibility describes the versatility of processes to adapt to new products.	Number of possible product variations that can be produced
Routing flexibility describes the redundancy of production resources.	Number of available resources

As mentioned, the implementation of all goals and variables in the same decision-making model would make no sense. Therefore, the following general criteria were defined to support developers in selecting relevant variables for sustainability-based production planning (Zarte et al., 2019c):

- The variable must be relevant regarding sustainable manufacturing for the considered production system and set system boundaries (model scope);
- The variable for sustainability must be improvable through actions for production planning (e.g., shifting or interrupting production activities, change of resource types);
- The variables must be independent of one another. Double counting of benefits or impacts (e.g., decrease in energy consumption, decrease in energy costs, and GHG emissions) must be avoided; and
- Data must be available and accessible for the selected variables considering production inputs and outputs.

4.3 Fuzzy Inference Model for Sustainability-Based Production Planning

Based on the general model scope (see Section 4.1) and the list of variables for sustainability-based production planning (see Section 4.2), the FIM was developed for sustainability-based production planning.

The FIM basic concept for production planning was documented in previous articles (see Zarte et al. (2018b)), illustrating the general model scope and a first model formulation for sustainability-based production planning. This concept was further developed and tested through an initial experimental study (see Zarte et al. (2021)). That experimental study was extended through the consideration of multiple sustainability goals and production scenarios.

The results are presented in this paper. For this approach, the section presents the formulation of the FIM:

1. The definition of membership functions for the fuzzification process,
2. The development of a rule engine selecting suitable fuzzy operators,
3. The definition of a function for the defuzzification process, and
4. The decision-making procedure for sustainability-based production planning.

4.3.1 Fuzzification

If suitable goals and variables have been selected for sustainability-based production planning (see Section 4.2), the three-step fuzzy model starts. For this approach, first, the selected variables need to be fuzzified. In general, the fuzzification process transforms the crisp values of a variable (x) into a dimensionless fuzzy value (μ_x) with the aid of fuzzy sets. A fuzzy set is used to interpret the concept subjacent to a selected variable, e.g., sustainability is low, medium, or high. A fuzzy set is mathematically formulated, and each element of the variable is mapped to a value between zero and one using a membership function (Zadeh, 1965).

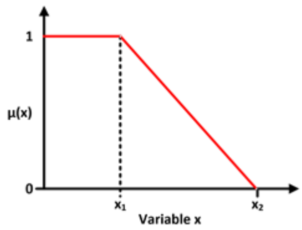
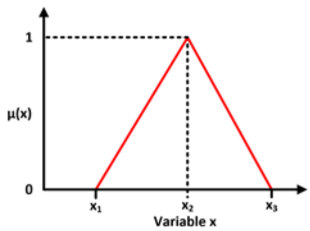
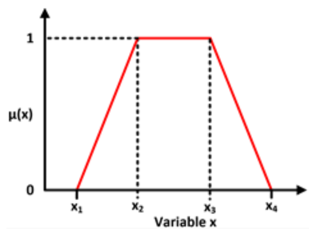
Variables for sustainable manufacturing originate in a variety of scales and units. Lower values mean better sustainability performance for some variables but worse sustainability for others. For example, sustainability improves when waste generation decreases but weakens when renewable energy demand decreases (Phillis and Kouikoglou, 2009). Therefore, the membership function must be carefully selected regarding the considered goal and the variable's nature for sustainability (Piluso et al., 2010). In general, there are two methods for the selection of fuzzy sets and their mathematical expression (Piluso et al., 2010):

- The subjective approach relies on collecting experience and knowledge from experts, where experimental data are incomplete and imprecise (e.g., determination of warm and cold room temperatures); and
- The data-driven approach clusters experimental data into subregions that can be linguistically interpreted as, for instance, low and high. Common data-driven methods include data clustering, machine learning, benchmarks, statistical analyses, mathematical models, and simulation experiments.

Sustainability assessments always need expert knowledge to determine the sustainability state (Saad et al., 2019). Production planning is a data-driven approach and requires information and communication technologies (Graves, 1999). Therefore, a combination of data-driven and subjective approaches is necessary for sustainability-based production planning because experts must combine the results of, e.g., simulation experiments with knowledge about sustainable manufacturing and, e.g., knowledge of green and safe working environments.

Fuzzy sets can help analyze subjective variable values, normalizing the assignment of values ranging from the most to the least desirable. According to the goal and variables' description and meaning, the fuzzy set shape must be carefully selected for each variable. The following three examples are given for the nature of the goals, variables, and the suitable fuzzy set shape (see Table 4.8).

Table 4.8: Fuzzy set examples related to the sustainability goal and variable.

Selection of the Fuzzy Shape	Graphical Presentation
The **Z-shape membership function** is appropriate for assessing variables that aim to minimize or constrain sustainability impacts (e.g., GHG emissions, production costs). For this membership function, the upper limit (x_1) and lower limit (x_2) need to be defined for the selected variables. The range between x_1 and x_2 presents the potential to minimize or constrain sustainability impacts.	
The **triangle membership function** is appropriate for assessing variables that aim to balance a variable at a specific value (e.g., peak power). For this membership function, the upper limit (x_2) and lower limits (x_1 and x_3) need to be defined for the selected variables. The range between x_1 and x_3 presents the potential to minimize or constrain sustainability impacts.	
The **trapezoidal membership function** is quite appropriate for assessing variables that aim to balance a variable within a specific range (e.g., recovery time). For this membership function, the upper limits (x_2 and x_3) and lower limits (x_1 and x_4) need to be defined for the selected variables. The ranges between x_1 to x_2 and x_3 to x_4 present the potential to minimize or constrain sustainability impacts.	

4.3.2 Inference

In the second step of the fuzzy model, the fuzzy values (μ_x) need to be combined. In general, the inference process combines fuzzy values using rules and fuzzy operators (Zadeh, 1965). For this approach, two general fuzzy rule inference models exist: individual rule inference modeling and composition rule inference modeling. Individual rule inference models are widely used for machine-control-automatization problems (fuzzy control) because the rules can be set for non-linear process parameters independently. This model was used in the paper by Zarte et al. (2018b). This paper showed that individual rule inference models´ complexity increases with the number of selected variables and defined fuzzy sets, which are less applicable for sustainability-based production planning. The FIM for production planning should be easily adaptable for new production situations, sustainability goals, and variables (see Section 4.2). Therefore, a composition rule inference model has been chosen for the FIM, which was presented in the paper by Zarte et al. (2021).

Next, a fuzzy operator must be selected to combine multiple fuzzy inputs. In general, three types of fuzzy operators exist for the aggregation process (Becker and Börcsök, 2000): the intersection operator (t-Norm), union operator (s-Norm), and average operator. Additionally, the fuzzy operator can be parametric or non-parametric, and multiple fuzzy operators can be combined to form a customized fuzzy function. However, parametric operators were not considered in this research. In general, the fuzzy operators have linguistically degrading or linguistically reinforcing effects on the model outcome. Therefore, the selection of the fuzzy operator is crucial in interpreting the FIM results. Experts must select the fuzzy operator according to the model's goal.

Based on the model´s framework for sustainability variables (Figure 4.3), the inference process consisted of two steps for the presented FIM:

1. The single sustainability improvement potential was determined by combining the variable for the state of sustainability and flexibility; and
2. The fuzzy values for multiple sustainability improvement potentials were combined to determine the overall sustainability potential to improve the production program.

The expected fuzzy output must be known for both steps related to the fuzzy input identifying the applicable fuzzy operator for the inference process. Therefore, a heatmap was developed to describe the expected output for combining the state of sustainability and flexibility (see Figure 4.5).

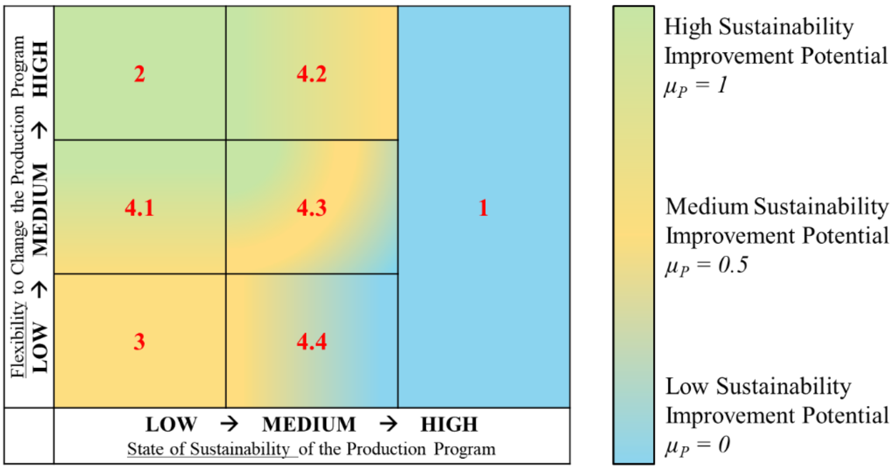


Figure 4.5: Expected fuzzy output for the sustainability improvement potential.

The heatmap is clustered in three colored areas representing different expected fuzzy outputs for the sustainability improvement potential to improve production programs (μ_P). The colored areas arose from the combination of the variables for the state of sustainability (x-axis) and flexibility (y-axis).

Based on the combination, the following logical rules were determined for the expected output (see numbering in the clusters of Figure 4.5):

1. IF [State of Sustainability, μ_S] is High, THEN
   [Improvement Potential] is Low ($\mu_P \rightarrow 0$).
2. IF [State of Sustainability, μ_S] is Low AND [Flexibility, μ_F] is High, THEN
   [Improvement Potential] is High ($\mu_P \rightarrow 1$).
3. IF [State of Sustainability, μ_S] is Low AND [Flexibility, μ_F] is Low, THEN
   [Improvement Potential] is Medium ($\mu_P \rightarrow 0.5$).

Moreover, four transition zones exist between the three main areas. These areas describe the sustainability potential between low, medium, and high:

4.1. IF [State of Sustainability, μ_S] is Low AND [Flexibility, μ_F] is Medium, THEN
[Improvement Potential, μ_P] is High-Medium ($\mu_P \rightarrow [0.5,1]$).

4.2. IF [State of Sustainability, μ_S] is Medium AND [Flexibility, μ_F] is High, THEN
[Improvement Potential, μ_P] is Medium-Low ($\mu_P \rightarrow [0,0.5]$).

4.3. IF [State of Sustainability, μ_S] is Medium AND [Flexibility, μ_F] is Medium, THEN
[Improvement Potential, μ_P] is Medium ($\mu_P \rightarrow 0.5$).

4.4. IF [State of Sustainability, μ_S] is Medium AND [Flexibility, μ_F] is Low, THEN
[Improvement Potential, μ_P] is Medium-Low ($\mu_P \rightarrow [0,0.5]$).

Common fuzzy operators were tested in EXCEL based on the defined fuzzy output, combining values for the state of sustainability (μ_S) and flexibility (μ_F). For the test, fuzzy value ranges (0,1) for the state of sustainability (μ_S) and flexibility (μ_F) were combined using a maximum, minimum, and arithmetic average fuzzy operator. The results are presented as a heatmap to visually compare them with the expected results (see Figure 4.6 to Figure **4.9**). The comparison shows that common fuzzy operators met the expected results partially for the FIM only (see red rectangle). Therefore, a customized fuzzy function was derived that represents the expected outcome for the FIM.

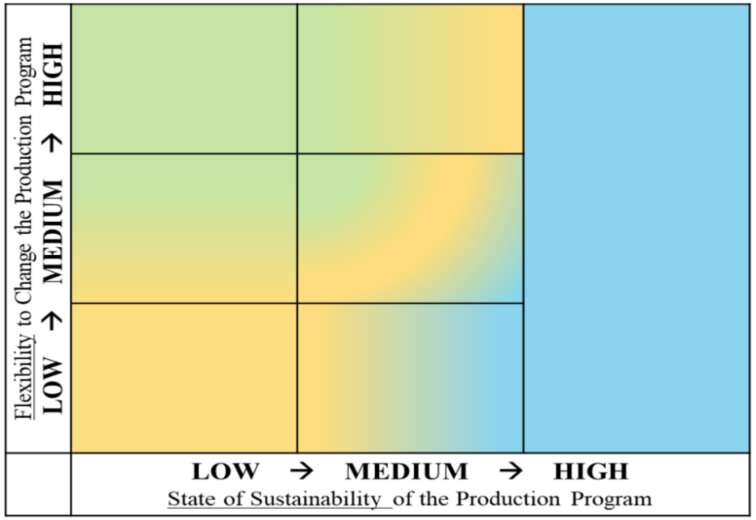


Figure 4.6: Expected Fuzzy Outcome.

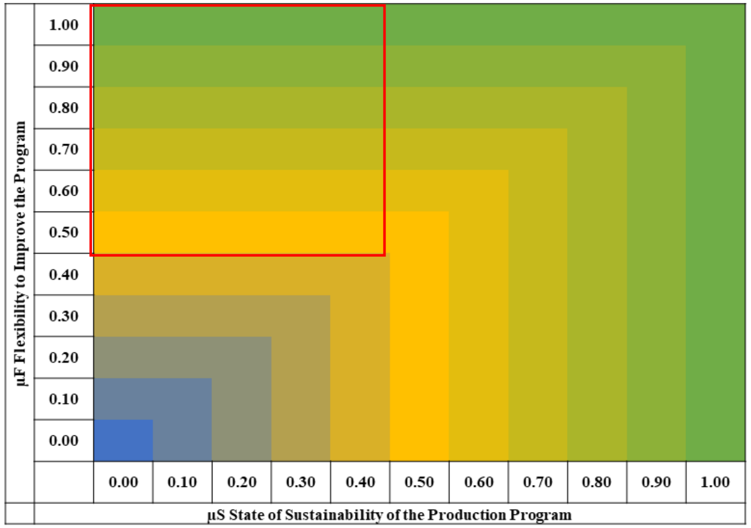


Figure 4.7: Fuzzy Outcome for the Union (Max.) Operator.

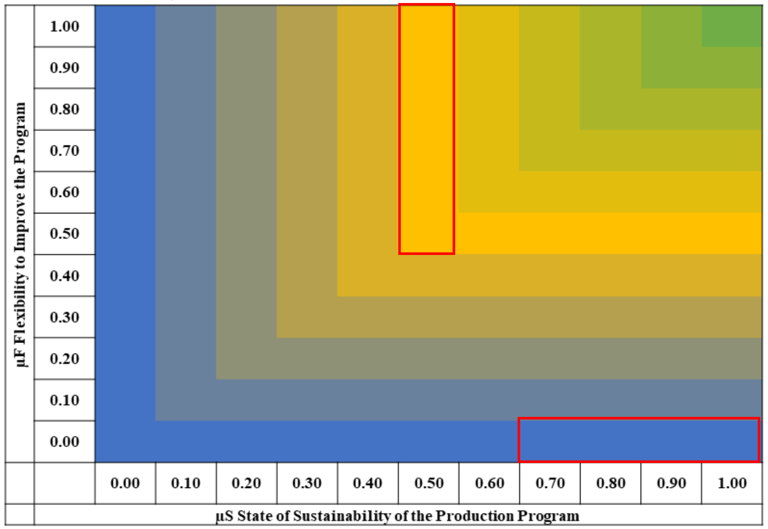


Figure 4.8: Expected Fuzzy Outcome for the Intersection (Min.) Operator.

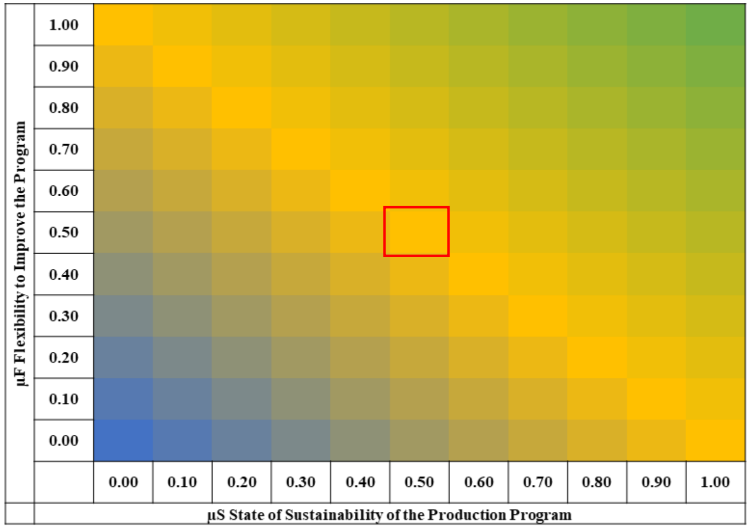


Figure 4.9: Fuzzy Outcome for the Average Operator.

For this approach, the following logical assumptions were made to select and combine suitable fuzzy operators:

- If the state of sustainability is high, the potential is low. Therefore, the complement of the variable ($\bar{\mu}_{S,j}$) state of sustainability had to be calculated (Equation 4.1).

$$\bar{\mu}_{S,j} = 1 - \mu_{S,j} \qquad \textbf{4.1}$$

- If the state of sustainability is high, no actions are necessary to improve the production program's sustainability. In this case, the flexibility variable could be ignored. Therefore, an intersection operator ($\mu_{\mu F \cdot \mu S}$) had to be selected to combine the complement of the state of sustainability and flexibility (see Equation 4.2).

$$\mu_{\mu F \cdot \mu S} = \mu_{F,j} \cdot \bar{\mu}_{S,j} \qquad \textbf{4.2}$$

- If the state of sustainability is low and flexibility is low, actions are necessary to improve the production program's flexibility. Therefore, an average operator ($MA_{\bar{\mu}}$) had to be selected to combine the complement of the state of sustainability and the intersection of the complement of the state of sustainability and flexibility (see Equation 4.3).

$$MA_{\bar{\mu}} = \frac{\bar{\mu}_{S,j} + \mu_{\mu F \cdot \mu S}}{2} \qquad \textbf{4.3}$$

Based on these assumptions, Equation 4.4 presents the customized fuzzy function to determine the sustainability potential ($\mu_{SP,j}$).

$$\mu_{SP,j} = \frac{1 - \mu_{S,j} + \mu_{F,j} \cdot (1 - \mu_{S,j})}{2} \qquad \textbf{4.4}$$

Figure 4.10 presents the heatmap combining the values for the state of sustainability and flexibility using the customized function. The comparison shows that the customized fuzzy function results (right) meet the expected results (left).

Expected Fuzzy Outcome **Outcome for Customized Fuzzy Function**

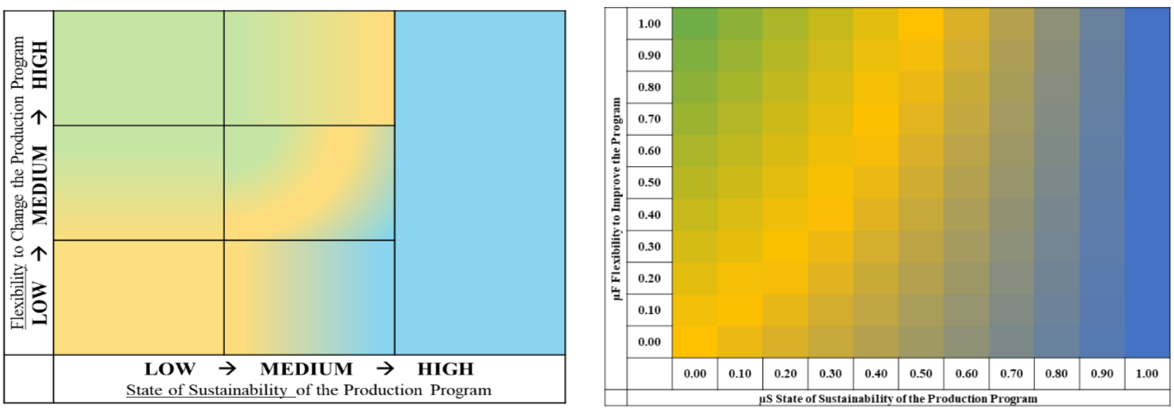


Figure 4.10: Combination of the fuzzy values using a customized function.

Next, the fuzzy operator needed to be defined to combine multiple variables for the overall potential to improve the production program (μ_{SP}). This operator was derived from the definition of sustainability-based production planning for this thesis. According to the definition, all production and sustainability goals must be achieved. Therefore, a union operator was selected because the union operators had a linguistically reinforcing effect that corresponded to the highest fuzzy value (see Equation 4.5). The highest fuzzy value indicates the highest potential to improve the production program.

$$\mu_{SP} = \bigcup_{j} \mu_{SP,j} = max(\mu_{SP,1}; \dots; \mu_{SP,j}) \qquad \textbf{4.5}$$

4.3.3 Defuzzification

In the third step of the fuzzy model, the combined fuzzy value (μ_{SP}) is defuzzified. In general, the defuzzification process converts the single fuzzy value back to a crisp value using a function (Zadeh, 1965). For this approach, several methods exist (see Section 3.3.1). The height method was applied for the FIM. This method defines an output function to determine the model outcome. Three potential states have been defined for the FIM outcome to interpret the combined fuzzy value: low, medium, and high. According to the expected aggregation output, the number of states is arrived at (see section before). The states have the following meanings and possible ranges:

1. **Low improvement potential** indicates a high state of sustainability. Therefore, no more action is required to change the production program. The range should be as close as required to zero because higher values decrease the planning effort to reach a low sustainability state.
2. **High improvement potential** indicates a low or medium state of sustainability and high production flexibility. Therefore, the production program can be adjusted to improve sustainability. According to the expected model outcome, the range should be between 0.55 and 0.75.
3. **Medium improvement potential** indicates a low or medium state of sustainability and low production flexibility. The production must be adjusted to increase production flexibility. The range is between low and high potential to improve the production program.

The nature of the functions affects the decision behavior of the model. Figure 4.11 presents one possible function for the defuzzification process using the height method. The presented function was also used to test the FIM for the experimental study. However, the ranges to determine the sustainability state of production programs need to be selected by experts carefully according to the model's scope. A further discussion of the defuzzification outcome is presented for a case example in Section 5.3.2.

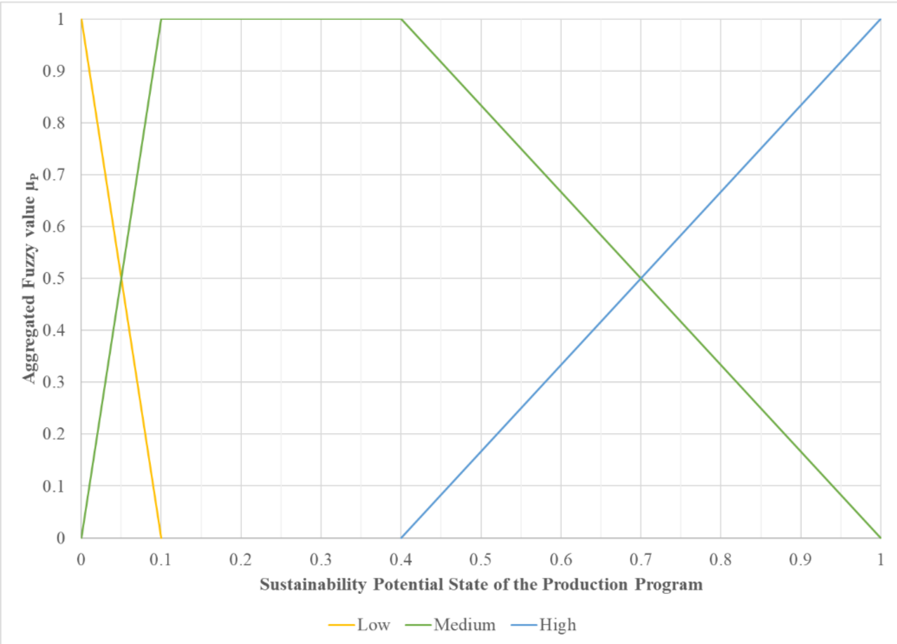


Figure 4.11: Defuzzification of the combined membership values.

4.3.4 Decision-Making Procedure

Finally, the results of the FIM needed to be interpreted. For this approach, Figure 4.12 presents a decision tree as a business process analyzing the FIM outcome for sustainability-based production planning. The assessment results are controlled in two steps:

1. The production goals are controlled:
   - If the production goals are not achieved ($f = 0$), the production goal variables need to be adjusted, and the sustainability assessment is repeated.
   - If the production goals are achieved, no actions are required.
2. The sustainability improvement potentials are controlled:
   - If a sustainability improvement potential is medium or high, the sustainability goal variable needs to be adjusted. For this approach, all sustainability variables are ranked according to their potential, identifying the highest sustainability improvement potential (union operator). The related variables need to be further controlled:
     - If the flexibility variable is low (μ_F = low), the flexibility variable needs to be adjusted, and the sustainability assessment is repeated.
     - If the flexibility variable is medium or high (μ_F = low, μ_F = medium), the sustainability variable needs to be adjusted, and the sustainability assessment is repeated.
   - If all production goals are achieved, and the sustainability improvement potential is low, no action is required, and the decision process is finished.

The following general recommendations can typically be given for adjusting the production program depending on the FIM outcome:

- Shift specific production activities.
- Interrupt production activities.
- Turn machines off or on.
- Increase the capacity of machines/human workforce.
- Use machines with lower resource demand.
- Use resources with lower sustainability impact.
- Exchange employees for specific production activities.

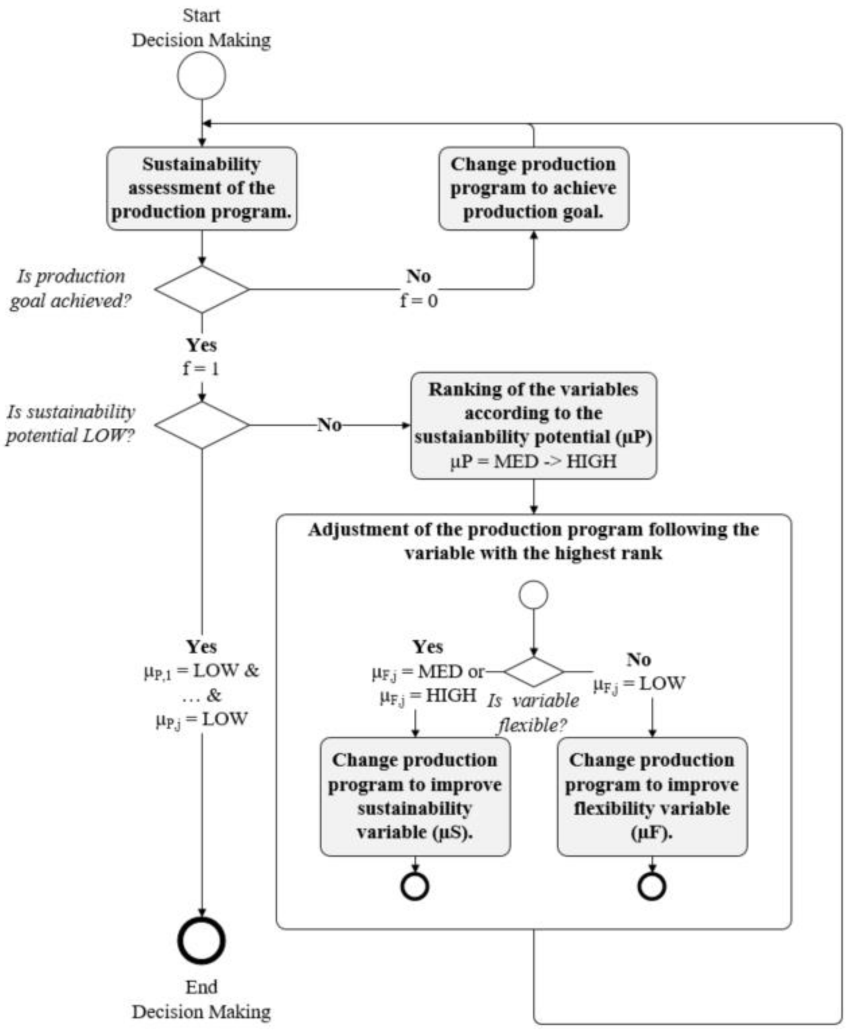


Figure 4.12: Decision-making process for sustainability-based production planning.

However, the recommendations must follow specific rules and criteria for sustainable manufacturing. For this approach, several basic management rule sets exist, which give guidelines based on politically initiated and socially legitimized sustainability concepts and strategies (Andes et al., 2019).

The German government proposed the first three basic management rules for sustainable acting (Enquete-Kommission, 1994):

1. **Regeneration rule:** The rate of extraction of renewable resources should not exceed their regeneration rates.
2. **Substitution rule:** Non-renewable resources should be used to the extent that equivalent alternatives are feasible only.
3. **Assimilation rule:** Emissions from consumption and production processes should not exceed the natural absorption capacity of the environment.

These rules have been further developed in several political discussions and conferences considering social aspects too (e.g., rules for generational equity, social responsibility, and knowledge integration). These new rules are part of the current German sustainability strategy (Bundesregierung, 2021) and are summarized by Umweltbundesamt (2017). However, the rules have hardly been relevant in practices formulating policies and strategies on process levels (Andes et al., 2019). Therefore, Kopfmüller (2011) developed substantive sustainability rules (see Table 4.9) as the minimum conditions for sustainable development (Kopfmüller, 2001). The rules give guidelines on how recommendations for strategic and operational planning should be designed in the decision support systems considering sustainability aspects.

Table 4.9: Overview of substantive sustainability rules (Kopfmüller, 2001).

General Sustainability Goals	Minimum Conditions (rules)
Securing human existence	- Protection of human health - Guarantee of basic services - Self-sufficient livelihood - Equitable distribution of opportunities for environmental use - Equalization of extreme income and wealth inequalities
Preservation of the productive potential of society	- Sustainable use of renewable resources - Sustainable use of non-renewable resources - Sustainable use of the environment as a sink - Avoidance of unjustifiable technical risks - Sustainable development of material, human, and knowledge capital
Preservation of the possibilities for development and action	- Equal opportunities with regard to education, occupation, and information - Participation in social decision-making processes - Preservation of cultural heritage and diversity - Preservation of the cultural function of nature - Preservation of social resources

4.4 Human-System Interface for Sustainability-Based Production Planning

In general, no widely accepted definition for the term human-system interface exists (Adam and Pomerol, 2008). Decision support human-system interfaces are front ends (e.g., platforms, dashboards, applications) for monitoring, analyzing, and optimizing users' specific activities to support their activities (Gröger et al., 2013).

A human-system interface is required to present the results of the FIM to the user. Zarte et al. (2019b) presented an example for a human-system interface for sustainability-based production planning. The prototype was further developed in this research.

4.4.1 Design Methodology

The standard ISO 9241-210:2010 exists to design computer-based interactive systems. The standard provides requirements and recommendations for human-centered design principles and activities throughout the designed systems' life cycle. For example, developers must emphasize users' needs and requirements for human-system interfaces to increase the system's efficiency, accessibility, and user satisfaction (ISO 9241-210:2010). Obviously, this principle already supports two dimensions of sustainability: social responsibility (user satisfaction) and economic success (system efficiency). Moreover, a human-centered design considers the complete life cycle of computer-based interactive systems, which includes impacts on the users but also the users´ environments (ISO 9241-210:2010).

The design, prototyping, and usability evaluation of the human-system interface for sustainability-based production planning follow a user-centered design procedure according to the standard ISO 9241-210:2010. The procedure is iterative and consists of five steps (see Figure 4.13).

In step 1 (identifying the needs of the user-centered design process), the goals and functions of the user interface are defined, and the users are identified. In step 2 (understanding and specifying the context of use), the user needs are specified, which involves the description of the user attributes, goals and tasks, and environment where the system will be used (see Section 4.4.2). Based on steps 1 and 2, step 3 (specifying system requirements) specifies the system requirements and architecture (see Section 4.4.3).

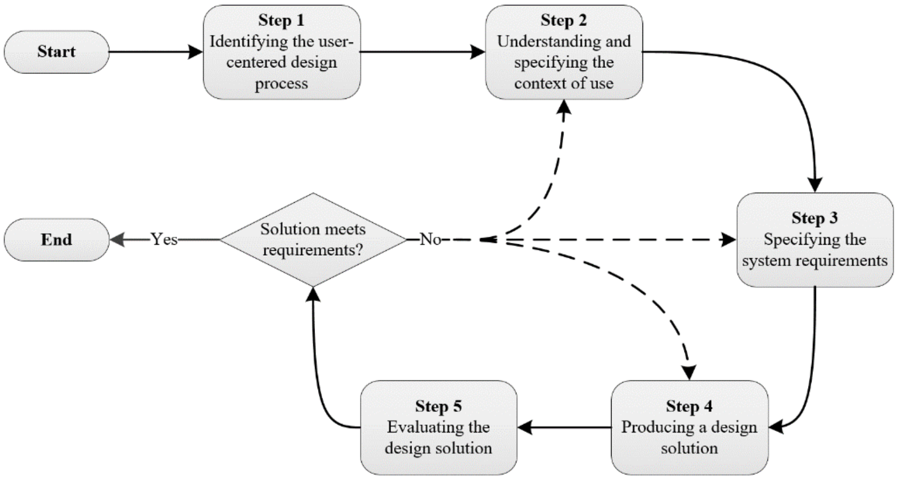


Figure 4.13: Iterative procedure to develop the user interface.

In steps 4 (producing design solutions) and 5 (evaluating the design solutions), design solutions are created and evaluated by experts and test users. The methods for the design and evaluation are adapted from the study by Nunes (2016). Three iterative steps were performed for the development of the user interface:

1. The first prototype was created on paper and provided examples about the visualization of the production plans and data, arrangement of active panels, buttons and diagrams, and the first content of additional information to evaluate the production plans. The paper prototype was evaluated through discussions with experts from production planning and system ergonomics. The results of this iterative step are not further presented and discussed in this thesis.
2. The second prototype was created with the aid of the online tool "Justinmind" (paid version) and provided the first functionalities to perform simple tasks. The digital prototype was evaluated with the usability test method cognitive walkthrough (Wharton et al., op. 1994) with non-expert test users. For the usability test, a scenario was developed, allowing a single interaction session without any flexibility for the test users. The prototype design and evaluation are presented in Section 4.4.4.
3. The third prototype was applied in an experimental study for sustainability-based production planning and was created with the simulation software AnyLogic® (The AnyLogic Company). The simulation contained the main functions and features for the decision support system for sustainability-based production planning. The user interface in AnyLogic® allowed the users to interact with a simulated production system in complex scenarios. The prototype design and evaluation are presented in Section 4.4.5.

4.4.2 User and System Requirements

The first step in the human-system interface design process is to study the human-system interface's intended users and required functions. It is necessary to know the type of people using the system (Nielsen, 1993). In general, several types of users are relevant to system development (Crowston, 2015). For this research, primary and secondary users were considered. The primary users are the system's main users and need all functionalities of the human-system interface. The secondary users need only partial functionalities of the system.

In general, methods for identifying the users can be categorized into two groups (Nielsen, 2013): data-based identification and assumption-based identification of users. Because of missing information about users for sustainability-based management systems, the users were identified and described based on interviews with experts for production planning and system ergonomics. The following three types of users were identified:

- User 1 (*production scheduler*) is a primary user and uses the system for sustainability-based production planning at periodical time intervals (daily, weekly) to improve the degree of sustainability of the planned production. The main attributes of this user are conventional production planning experience and knowledge about the economic, environmental, and social consequences of actions to improve the sustainability of the production program. The user must be able to consider the sustainable impacts of the planned production, control the planned production performance according to sustainable goals, and modify production plans to meet target production performances and sustainable goals.
- User 2 (*production manager*) is a secondary user and uses the system for sustainability-based production planning at periodical time intervals (weekly, monthly, quarterly) to control the previous production performance with target performances. The user needs experience in conventional production controlling. Moreover, the user must be able to compare the performance of previous production inputs and outputs with target inputs and outputs.

- User 3 (*manager for environmental and sustainable topics)* is also a secondary user and uses the system for sustainability-based production planning at periodical time intervals (monthly, quarterly, yearly) to report and analyze sustainable impacts of the production and control sustainability status goals. Similar to the production manager, this user needs experience in conventional production controlling. Moreover, the user needs knowledge about sustainable impacts from competitors using similar processes (e.g., analyzing sustainability reports). The user must be able to analyze and present production inputs and outputs for sustainable reporting, compare resource consumptions and emissions of a single consumer (present values with historical values for specific timeframes), and compare the resource consumption and sustainable impacts of two or more consumers (internal and external benchmarks).

4.4.3 System Requirements and Architecture

The following system requirements and functionalities represent the basis for the development of the human-system interface for sustainability-based production planning based on the user needs above:

- *Graphical presentation of production plans:* With the aid of time-diagrams, the considered production plan (historical and planned production) of specific production resources (machines, employees, external services), products, and customer orders must be presented for specific timeframes (day, week, month, year). Moreover, relevant information, such as the start and end times of production steps, required resources (e.g., energy, materials), and deadlines of customer orders, must be available for the users.
- *Graphical presentation of production data and sustainability variables:* With the aid of time diagrams and related to the considered production plan (historical and planned production), production data (e.g., energy demand, renewable energy production) and sustainability variables (e.g., self-consumption ratio) must be presented for specific timeframes (day, week, month, year).
- *Presentation of the state of sustainability:* With graphic elements, the state of sustainability must be presented for the considered production program.
- *Adjustment of production steps:* With the aid of data inputs, the start, end, and process times of production tasks and orders must be changeable to improve the state of sustainability of the considered production program.
- *Security of the system*: With the aid of user rights, the functionalities and information contents of the human-system interface for sustainability-based production planning, such as adjustment of production steps and the presentation of specific historical production plans, must be allocated to specific users.

The user interface aimed to act as a front-end system for the users to present the results of the FIM for sustainability-based production planning. For this approach, the user interface presents data and information from the production system, production management system, and other required systems.

Figure 4.14 presents the structure of the decision support system as part of a cyber-physical system (CPS).[1] According to the standard (DIN SPEC 91345:2016-04, 2016) for the reference architecture model industry 4.0 (RAMI4.0), the architecture of the user interface was structured in layers that represent physical parts (red background) and virtual parts (green background) of the CPS. The feedback loops are presented as lower and upper arrows.

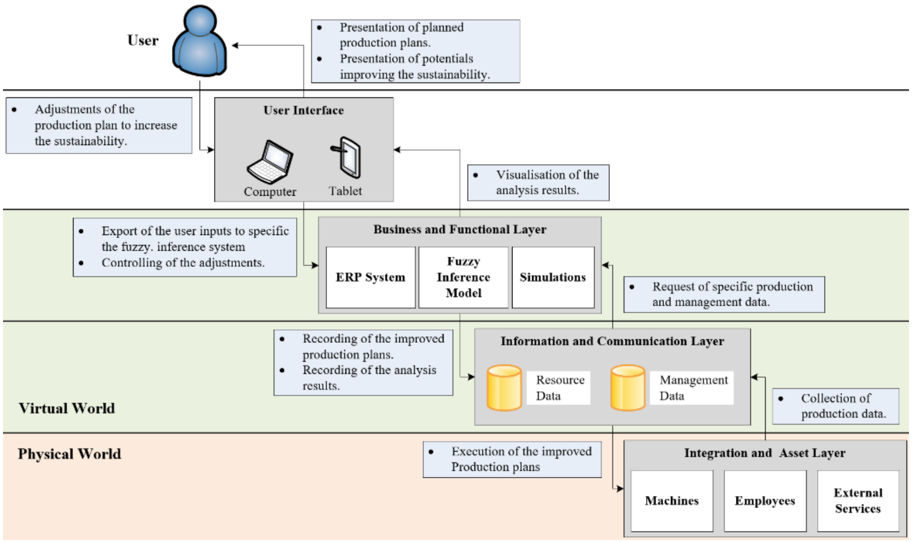


Figure 4.14: System architecture for sustainability-based production planning.

The i*ntegration and asset layer* contain the production system to produce the production output, including machines, employees, and external services. With the aid of information and communication technologies (ICT), production data are collected (upper arrow), and production tasks are received (lower arrow).

The *information and communication layer* retrieves the production data from the asset layer and records that data into databases. With the aid of database queries, specific information requests (upper arrow) and management data (e.g., production plans, evaluation results) are recorded (lower arrow).

The *business and functional layer* contains models and systems to plan, analyze, and optimize the production system, such as the FIM, enterprise resource planning (ERP) system, and the virtual renewable energy power plant. With the aid of the user interface, the business and

[1] A CPS is an integration of computation with physical processes. Embedded sensors, computers, and networks monitor and control the physical processes, usually with upper and lower feedback loops where physical processes affect computations Lee (2008).

functional layer results are visualized to the user (upper arrow), and adjustments in production plans are made by the user to improve the degree of sustainability (lower arrow).

4.4.4 First Prototype Design in Justinmind

Figure 4.15 presents the first digital prototype of the main system for sustainability-based production planning. The figure not presents, for instance, model configuration pages, data input pages, are required to set up the model. A normal user log-in is required to access the platform. Through the user log-in, different user rights can be allocated to users, limiting the human-system interface's functionality. The platform for sustainability-based production planning can be separated into three parts (part a, b, and c), which contain buttons (red rectangles), active panels (blue rectangles), and time diagrams (green rectangles).

Figure 4.15: User interface for sustainability-based production planning in Justinmind.

Part a provides basic functionalities (“Undo,” “Redo,” and “Logout” buttons) and information (current time, date, and logged-in user) to the user. Moreover, the user can specify the timeframe for production planning through the data-input fields.

Part b presents the production plan as a Gantt-time diagram and additional information in the active panel. With the button “Select Resources,” the active panel is changed to a tree-node menu that contains lists of the involved resources, products, and customer orders for the specified timeframe. The user can choose which resources, products, or customer orders are presented in the Gantt-time diagram using checkboxes. The Gantt-time diagram is refreshed with the button “Show Production” and shows the user's selection. With a click on one of the colored bars, the active panel shows additional information to the selected production task. The user can see the process name, customer order ID, deadline of the customer order, start and end time of production steps, process time, and required resources (e.g., employees, energy demand). The user can change the start time of the production task through dragging and dropping the colored bar or via an input field in the active panel for the start time. For production steps with changeable process times (e.g., idle time of machines), the processing time can be changed through an input field in the active panel, which changes the length of the colored bar. Because of the limited functionality of the Justinmind prototyping software, it was not possible to connect production tasks. If production tasks can only perform if previous tasks are finished, start times must be automatically changed in the whole production program. This feature must be implemented in future prototypes.

Part c presents the production data and sustainable variables as a line-time diagram and additional information for the state of sustainability in the active panel. With the button “Select Indicators,” the active panel is changed to a tree-node menu that contains lists of the available production data and sustainable variables for the specified timeframe. The user can choose which production data and sustainable variables are presented in the line-time diagram using checkboxes. The line-time diagram is refreshed with the button “Show Indicators” and shows the user's selection. In the active panel, the user can see the state of sustainability (as a value, linguistic value, or bar chart), best-practice sustainability score, target sustainability score, and a list of sustainable variables with linguistic values for the considered timeframe. The list of sustainable variables is sorted according to the linguistic values and shows the highest potential for improving the state of sustainability at the top. Because of the limited functionality of the tool Justinmind, it was not possible to connect production tasks with the production data and sustainability variables. If the start time of a production task is changed, the values in the line-time diagram must be automatically changed, and the new state of sustainability must be presented. This feature must be implemented in future prototypes.

A scenario was developed to test the usability of the human-system interface. The test users performed tasks with the aid of the human-system interface in the scenarios.

For the scenario, six tasks were defined:

1. Log in to the human-system interface with the username “User1” and the password “1234.”
2. Choose the start and end date 01/01/2018, start time 04:00, and the end time 20:00.
3. Select all available resources, products, and customer orders and consider the production plan.
4. Select all available production data and sustainable variables and consider only the historical information in the diagram.
5. Change the start time of the production task “Product 2” (Resource #2) to 06:00.
6. Change the processing time of the production task “Idle Mode” (Resource #1) to 0.5h.

For the usability test, four test users were selected. The test users were students from the industrial engineering faculty who had no practical experience in production management and sustainable manufacturing. The usability test procedure was as follows. First, the test users were introduced to the tasks and goals of the primary user, the “Production scheduler” of the human-system interface for sustainability-based production planning. Second, the test user performed the defined scenario. During the tests, the test users received no support to perform the tasks, and the time was recorded for how long the test users needed to perform the tasks. After performing the defined tasks, third, the test users gave feedback about problems that occurred during the test and gave recommendations for improvements. The feedback and recommendations from the tests users are discussed here and classified to the Nielsen heuristics (Nielsen, 1995) to identify potential fields for improving the human-system interface for sustainability-based production planning.

The Nielsen heuristics *“Help and documentation,” “Help users recognize, diagnose, and recover from errors,”* and *“Error prevention”* consider the support and feedback for the user in case of errors and problems with functionalities. The prototype contained no support and error feedback systems, functionalities that must be implemented in future prototypes to meet these heuristics.

The Nielsen heuristic *“User control and freedom”* considers functionalities to leave unwanted states without having to go through an extended dialogue (e.g., "Undo" and "Redo" buttons). The prototype contained buttons for undo and redo but without functionality. This functionality must be implemented in future prototypes.

According to the Nielsen heuristic *“Match between system and real world,”* the system should speak the users' language, with words, sentences, and concepts familiar to the user, rather than system-oriented terms. This heuristic can only be considered in a limited manner because non-expert users were selected for the usability tests. Therefore, the test users were not familiar with the concept of sustainability and production planning. Despite this limitation, the test users offered the criticism that the system language was not native. Non-expert users who were not familiar with English terminology for production planning in particular had problems understanding the meanings of, for example, buttons and diagrams for the presentation of the production plan. In future prototypes, optional languages and a glossary for important words should be provided to increase the usability for non-expert users. Moreover, future prototypes must be tested with expert users to consider this heuristic from another perspective.

The Nielsen heuristic *"Recognition rather than recall"* considers the user's memory load by making objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. The test users missed the functionality to compare various timeframes. Moreover, implementing a second screen to specify timeframes and select resources, products, customer orders, production data, and sustainable variables was discussed to decrease the information content. A sequence must be implemented to set the Gant-time and line-time diagrams in future prototypes.

The Nielsen heuristic *"Flexibility and efficiency of use"* considers if accelerators (e.g., shortcuts) are used to speed up the interaction with the human-system interface. The test users suggested labeling and marking the production tasks in the Gant-time diagram to indicate possible interactions with the bars in future prototypes. Moreover, useful shortcuts could be implemented to increase the speed of interacting with the platform.

The Nielsen heuristics *"Aesthetic and minimalist design," "Consistency and standards,"* and *"Visibility of system status"* consider the design and information content of the prototype. The test users were satisfied with the design of the prototype. The information content was sufficient to perform the user tasks without help in an acceptable timeframe.

Table 4.10 presents the times which the users spent to perform the tasks. These times were compared with the reference time of an expert user (developer of the system) and show that there is still space to improve the intuitive operation of the platform to decrease the time performing specific tasks. These results can be used as a basis for future usability tests of new prototypes.

Table 4.10: User test results performing the tasks.

User	Time [mm:ss]	Difference to the Reference User [mm:ss]
Reference User	01:57	+/- 00:00
Test User 1	07:15	+ 05:18
Test User 2	05:57	+ 04:00
Test User 3	08:26	+ 06:29
Test User 4	04:02	+ 02:05

4.4.5 Second Prototype Design in AnyLogic

Figure 4.16 presents the second digital prototype of the human-system interface for sustainability-based production planning developed in AnyLogic®. The second prototype was designed based on the concept and evaluation results presented in Section 4.4.3. Moreover, the interface contained computations and features missing in the first digital prototype. The user interface was structured into three main elements that provide different functions to the users.

The first element (1) allows users to select different views on the simulation model presenting the simulation results ("Main"), 2D visualization of the simulated production systems, the logic of the discrete event simulation, and the computations of the decision support system. However, the Main view presents the user all the required information and decision support for sustainability-based production planning. The other views are helpful in case of simulation issues.

The second element contains the main results of the decision support system in the form of text information. The user can select different FIM result views using radio buttons on the left side (2.1). The information presents whether production and sustainability goals are achieved or recommendations on how to improve the planned production´s sustainability (2.2). Moreover, the planned production is presented as a Gant chart next to the recommendations.

The third element presents additional data about the planned production. The production data view can be changed using radio buttons on the left side (3.1). The production data are presented using Gant and line charts (3.2) and provide the user information about the production performance, energy data, inventory data, and human workload. These data are helpful for reporting and benchmarking the production system.

However, this research aimed to develop and demonstrate a decision support system for sustainability-based production planning. Therefore, the FIM result views (2) were presented in more detail. The views were structured as follow:

- Decision-Making
- Defuzzification
- Inference
- Fuzzification
- Variables (Sustainability)
- Variables (Production Goal)

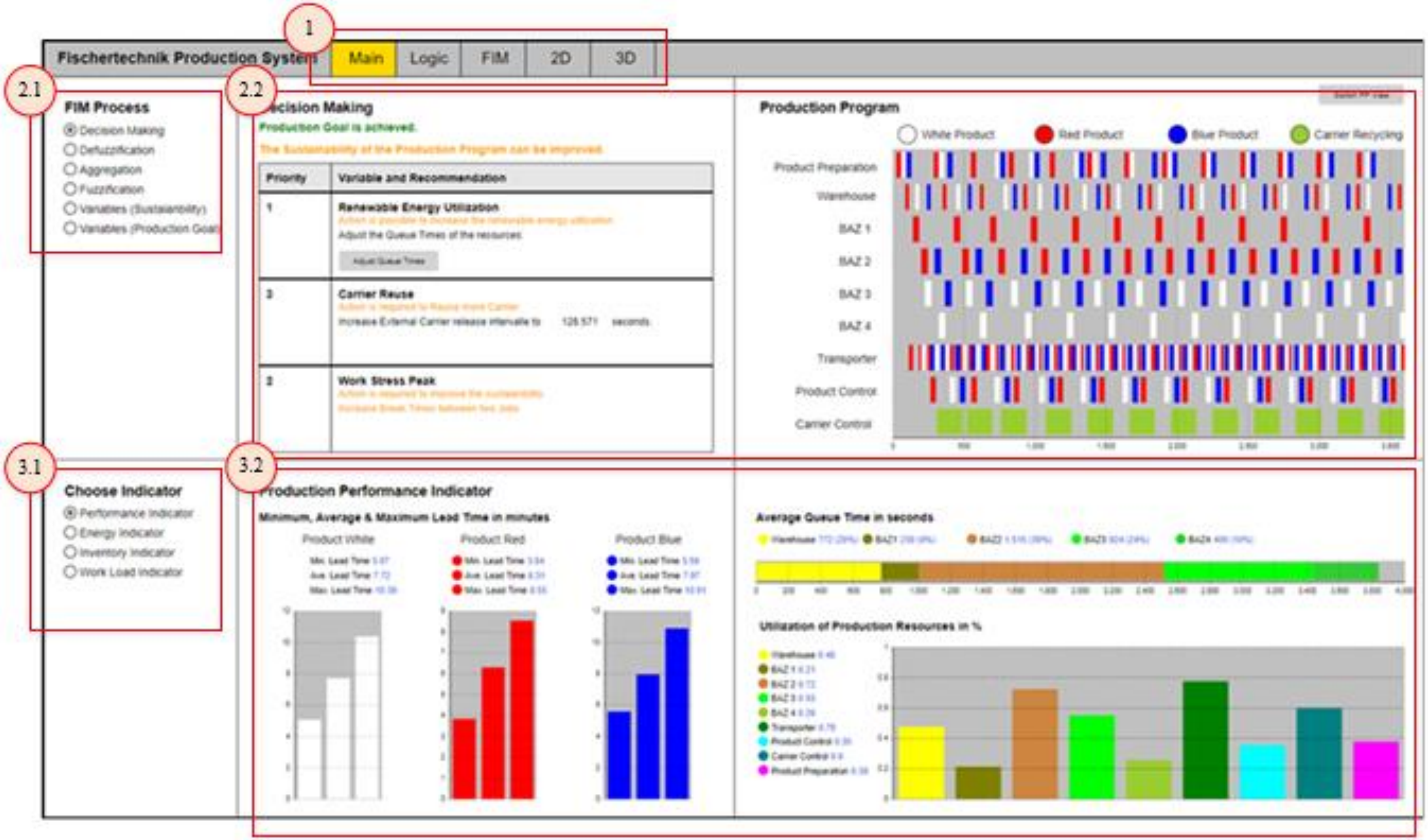


Figure 4.16: User interface for sustainability-based production planning in AnyLogic®.

After a simulation, first, the user saw the main results of the decision support system in the form of text information for the goals and recommendations on how the production program can be improved (see Figure 4.17). The status gave information about:

- if the production goals were achieved (see figure left), and
- if the sustainability goals were achieved (see figure right).

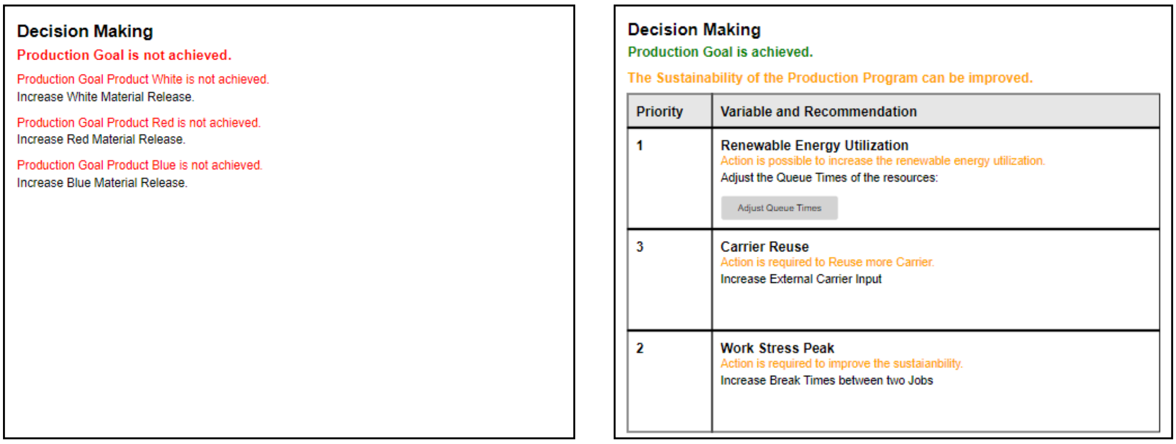


Figure 4.17: Decision-making views: Production goal (left) and sustainability goal (right).

When the production or sustainability goals were not achieved, recommendations were given on how the goals could be achieved. For example, the decision support system recommended increasing the material input to the production system.

For the sustainability goals, the recommendations were presented in the form of a table. The table prioritized improving specific variables where the value “one” means low priority and “three” high priority. The priority determination was part of the decision-making procedure (see Figure 4.12) and reflected the rank of the sustainability goal. Moreover, the table gave specific recommendations for improving the production program.

If the user wanted to understand the reasoning for the recommendations, the user could check the single FIM steps (see Table 4.11).

Table 4.11: Description and views for the decision-making process

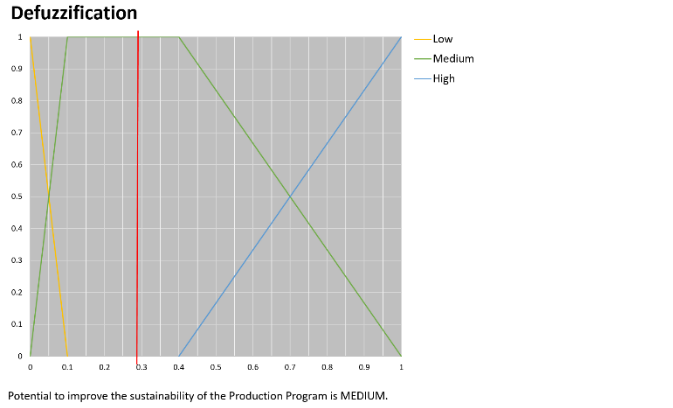
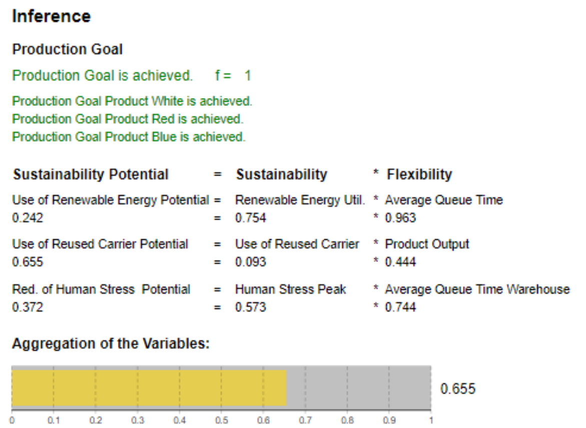
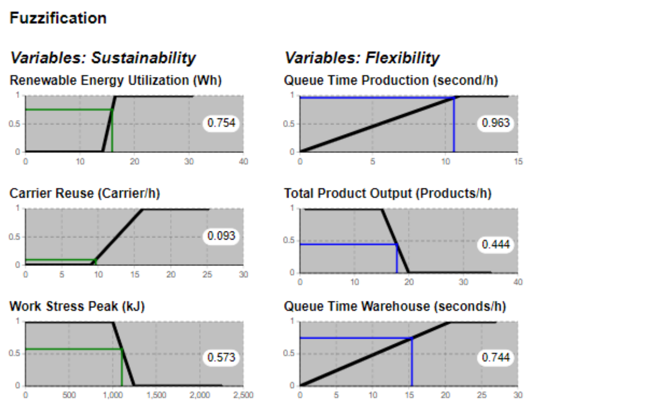
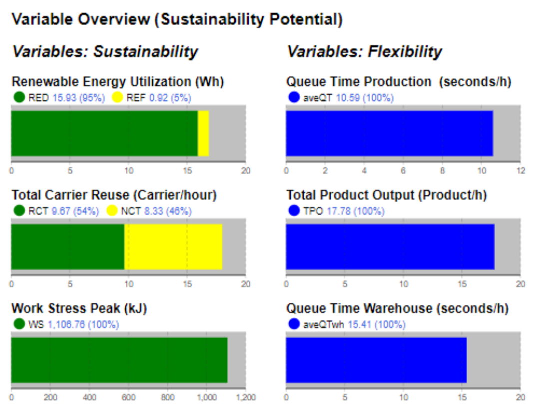
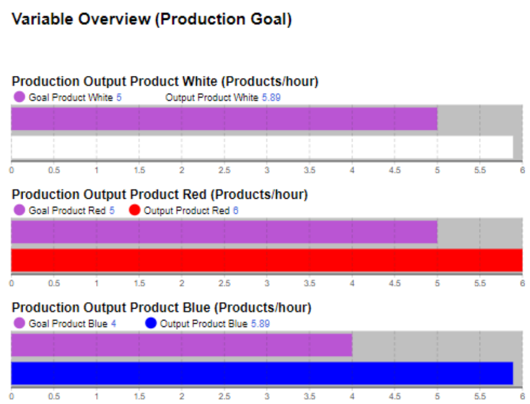
View Description	User Interface View
The **defuzzification** view shows the transformation of the fuzzy inference value in a linguistic expression (low, medium, or high), determining the overall improvement potential of the production program as text information. If the production goal is not achieved, no result for the defuzzification is presented because the production goals need to be achieved first.	
The **inference** view gives detailed information about production goals variables and the aggregation of single fuzzy values for sustainability and production flexibility. Moreover, the final fuzzy inference value is presented as a Gant chart.	
The determination of the single fuzzy values is presented in the **fuzzification** view. This view is structured in two columns. The first column presents the fuzzy sets for the sustainability variables as line diagrams. The second column presents the fuzzy sets for the production flexibility variables.	

Table 4.11: Description and views for the decision-making process (continued).

View Description	User Interface View
The **variable overview (sustainability potential)** view presents an overview of all sustainability and production flexibility variables. The variables are presented as Gant charts. Moreover, the Gant charts present additional information about possibilities for improving the production program.	
The **variable overview (production goal)** view presents an overview of all production goal variables. The variables are presented as Gant charts. Moreover, the Gant charts present additional information about planned production goals.	

5

Experimental Study for Sustainability-Based Production Planning

A detailed description of the experimental study of the decision support system for sustainability-based production planning is presented in this section. The section aims to give a description of the decision support system implementation and a discussion of the study results.

The structure of the sub-sections is as follows. Section 5.1 presents the goal and scope of the experimental study. The section also gives an overview and analysis of the learning factories´ production system. Based on the scope, the fuzzy set configuration is presented in Section 5.2. The section gives detailed descriptions of how the available production data have been used to configure the FIM. The decision support system concept is proven in Section 5.3. For this approach, production planning scenarios are simulated to demonstrate the functionality of the decision support system. Moreover, the study results are presented and discussed. Based on the results, general implications are defined for sustainability-based production planning in Section 5.4).

5.1 Scope of the Experimental Study

The experimental study was performed using an AnyLogic® simulation model of an experimental setup based on a learning factory. The following subsections present the physical and digital structure of the learning factory, goals, and system boundaries for the experimental study testing and validation of the decision support system for sustainability-based production planning.

5.1.1 Physical and Digital Structure of the Learning Factory 4.0

The Learning Factory 4.0 was developed in the production-planning lab of the University of Applied Life Sciences Emden/Leer and demonstrates a typical repetitive production process producing several kinds of products, using Fischertechnik® modules (Zarte et al., 2019e). The learning factory is used to teach students in digital production management and in research projects to develop and test new solutions for digital manufacturing. However, the following descriptions present relevant functionalities of the learning factory for the experimental study. additional information can be found in the literature (Pechmann et al., 2019; Zarte et al., 2019e)

The physical production system consists of the following typical production modules: a warehouse, four working stations, transport systems, and a quality control station (see Figure 5.1). Each production module is connected via the programmable logic controller (PLC) to a Raspberry Pi. The PLC controls the production station activities of a production module. The Raspberry Pis are responsible for the communication among the production modules (machine to machine communication, M2M) and the enterprise resource planning (ERP) system (machines to business process communication, M2B). For this approach, the ERP system Transfact® is used to plan and control production activities conventionally. The learning factory produces wooden cylinders in different colors. The material is transported using black carriers.

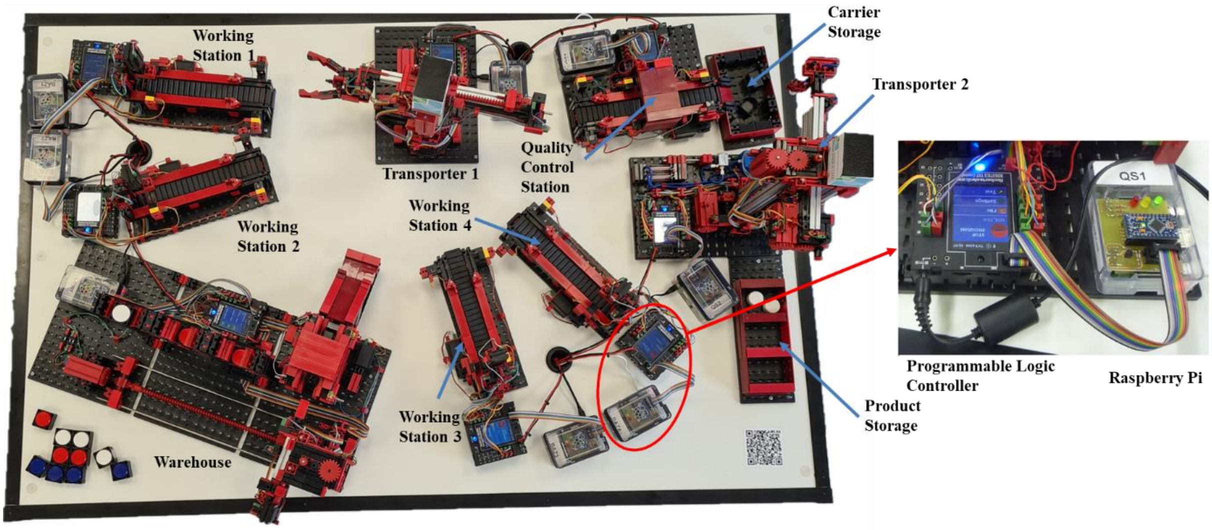


Figure 5.1: Physical structure of the Learning Factory 4.0.

The underlying concept for the digitalization of the Learning Factory 4.0 is following a service-oriented architecture approach (Colombo, 2014). The production stations (working stations, transporter, warehouse, quality control) are implemented as individual functional objects, which can act self-contained and independently from one another. Each production station exposes its specific functionalities in the form of web services to interact with other stations forming individual production processes (see Figure 5.2).

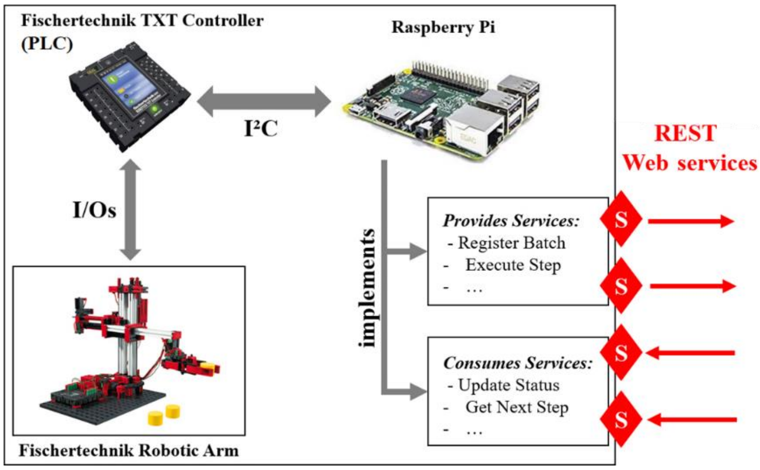


Figure 5.2: Digital structure of the Learning Factory 4.0.

A production procedure works as follows. Products are ordered in the ERP system Transfact®. The Raspberry Pi from the warehouse pulls a list of open production orders from the ERP system via web services using a REST interface. The orders contain information about the articles to be produced and their corresponding production steps. Each production step is subscribed and unsubscribed in the ERP system by the corresponding Raspberry Pi of a production module. Therefore, the current production status is always reflected in the ERP system. In the next step, the Raspberry Pi of the warehouse sorts the open orders internally by ascending lot numbers. According to this order, the products are released from the warehouse by starting the desired production program on the PLC to release the material automatically. After the material has been removed from storage, the warehouse subscribes the material to the transporter. The transporter moves the material to the appropriate workstation. After the product has been processed at the workstation, the material is sent back to the transporter, moving the material to the next production station. All these production steps are controlled and subscribed in the ERP system. If the product is finished, the transporter moves the product to the quality control station. The quality control checks the color of the delivered product and separates the stone from its carrier by a pneumatic transport system. The stone is stored in a storage area according to its color.

For production planning and controlling purposes, an energy management system has been implemented in the Learning Factory 4.0 (Zarte and Pechmann, 2017). The energy management system consists of:

- an energy measuring system, which measures and stores energy demand data from production activities (Zarte and Pechmann, 2020), and
- a virtual renewable energy power plant that simulates data from the local weather station and renewable energy plants (photovoltaic, wind plant, storage) from the University of Applied Sciences Emden/Leer (Pechmann et al., 2016; Woltmann et al., 2018).

The Learning Factory 4.0 ERP system and energy management system provided the required data and information to develop the simulation model for the experimental study.

5.1.2 Simulation Model of the Learning Factory 4.0

As mentioned above, the Learning Factory 4.0 represents a typical repetitive production process producing several kinds of products. A repetitive production is usually used to produce standard items that are produced in large quantities but small lot sizes. The production is planned and executed based on a schedule consisting of planned orders. The production process is controlled with the schedule and related production goals (Wieneke and Schmidt, 2012).

The repetitive production activities of the Learning Factory 4.0 were transferred to a simulation model producing three products (white, red, and blue). For this approach, the simulation software AnyLogic® was used (see Figure 5.3). Moreover, the simulation model was extended by additional processes enabling sustainable manufacturing (e.g., renewable energy use, disposal or reuse of materials, worker fatigue). These extensions are further explained later in this section.

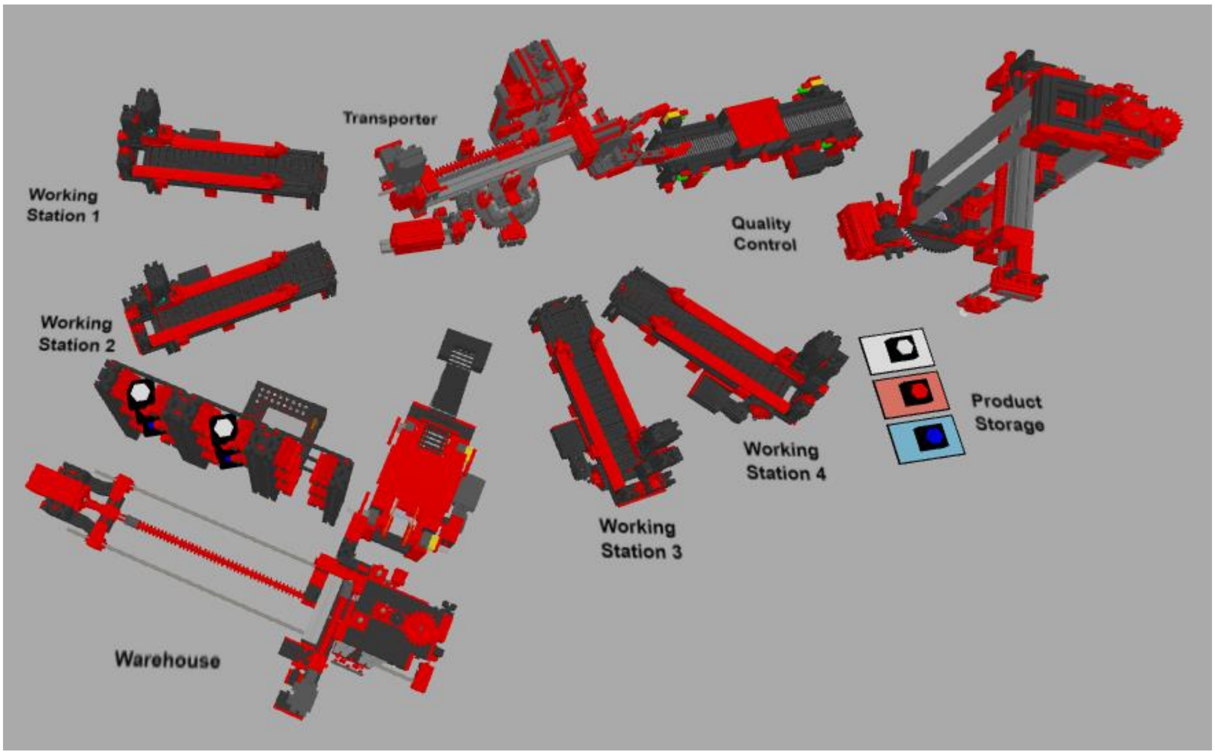


Figure 5.3: 3D Simulation model of the Learning Factory 4.0.

The simulation model was developed using data and information from the ERP system Transfact® and real production data from the Learning Factory 4.0 to represent the physical system as a digital twin. In general, a digital twin can be defined as “a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases" (Stark and Damerau, 2019). Moreover, digital twins can be categorized according to their possibility to communicate with the physical twin (Kritzinger et al., 2018):

- No communication (digital model),
- Communication from the physical to the digital twin only (digital shadow), or
- Communication between the physical and digital twin in both directions (digital twin).

In the case of the Learning Factory 4.0, the physical twin can partially communicate with the digital twin. Therefore, the developed simulation model can only be characterized as a digital model. This digital twin category was sufficient for testing the functionality of the decision support system.

Figure 5.4 presents the relevant production sequences and material flows of the Learning Factory 4.0 for the experimental study. The production sequences are represented where production activities are shown as containers, and transportation steps are shown as arrows between the containers. The material inputs are displayed on the left side in the figure: white stone, red stone, blue stone, new carrier, and external carrier. The product and carrier waste output is displayed on the right side. The material input is controlled using a schedule in the form of an arrival table (order list) in a database. The arrival table contains time information about releasing stones and external carriers to the material preparation production activity.

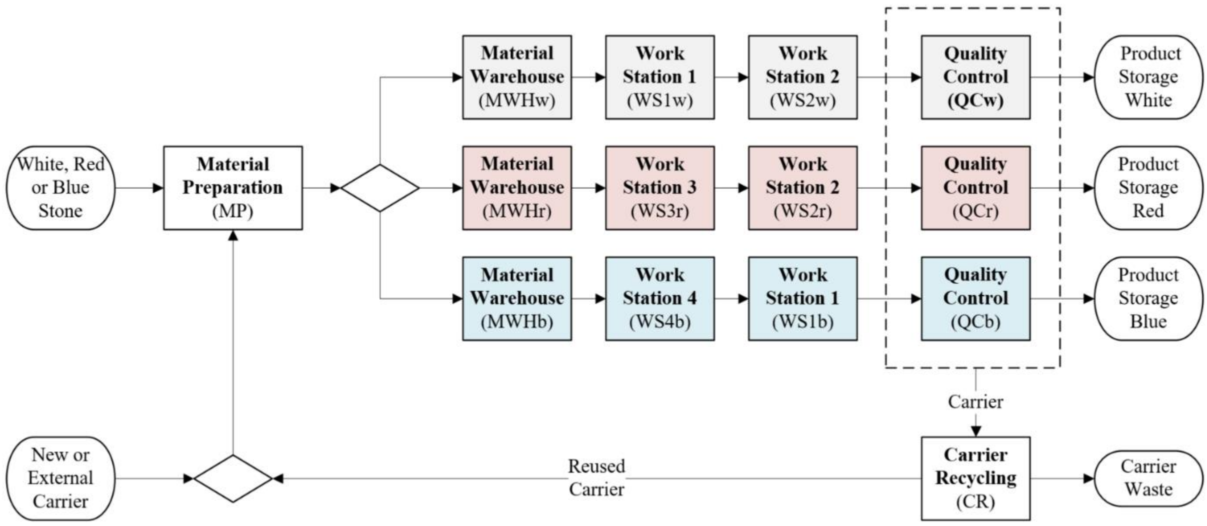
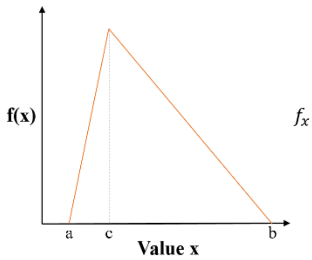


Figure 5.4: Production sequence and material flow of the Learning Factory 4.0.

All production activities have individual processing times and energy demands, which are recorded in a production database. For the simulation model, statistical analyses were made to determine the random distribution of the processing times and energy demands. The distribution is modeled as a triangular distribution (see Figure 5.5). The triangular distribution is often used when no or little data is available. Therefore, it is rarely an accurate representation of a data set. However, the triangular distribution is a good model for skewed distribution datasets (Johnson, 1997).



$$f_x = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}, if\ a \le x < c \\ \frac{2}{b-a}, if\ x = c \\ \frac{2(b-x)}{(b-a)(b-c)}, if\ c < x \le b \end{cases}$$

Figure 5.5: Formulation of the triangular distribution (Johnson, 1997).

The triangular distribution is determined for a dataset of the value x, calculating the minimum value (a), the maximum value (b), and the mean value (c). Table 5.1 presents the triangular distribution values for the processing time and energy demand. The requirement of human workforces is presented for the production stations. However, the presented energy demands should give an idea about the ranges only. The simulation model uses the actual energy demand profiles, modelling the processing energy demand of production activities. The production modes startup, shutdown, and idle modes were not considered for the simulation model. It was assumed that the machines are offline before and after production activities to save energy.

Table 5.1: Processing times and energy demands of the Learning Factory 4.0.

Index/ Machine	Processing Time (seconds)			Energy Demand (W)			Human Workforce Required?
	Min. (a)	Max. (b)	Ave. (c)	Min. (a)	Max. (b)	Ave. (c)	
MP	32.5	37.5	35.0	0	0	0	Yes
MWHw	57.45	58.00	57.67	5.242	5.247	5.245	No
WS1w	24.55	26.40	25.15	4.365	4.426	4.395	No
WS2w	23.00	24.65	23.62	4.534	4.662	4.562	No
QCw	31.45	34.85	32.10	8.092	8.223	8.182	No
MWHr	52.45	52.55	52.50	5.209	5.216	5.212	No
WS3r	22.10	26.40	23.367	4.596	4.798	4.657	No
WS2r	23.15	25.15	23.91	4.515	4.640	4.554	No
QCr	38.30	40.25	39.25	8.086	8.135	8.106	No
MWHb	50.55	50.65	50.60	5.209	5.218	5.214	No
WS4b	24.65	26.40	25.72	4.549	4.588	4.566	No
WS1b	24.40	26.40	25.62	4.408	4.442	4.429	No
QCb	41.80	42.85	42.52	8.079	8.109	8.097	No
CR	0	0	0	0	0	0	No
Tran.	-	-	-	2.421	2.464	2.446	No

The simulated product lead time and energy demand were verified by comparing the simulation results with three physical production scenarios. The following scenarios were used:

- Production of six white products,
- Production of six red products, and
- Production of six blue products.

For the scenarios, all products were simultaneously released to the production system and processed. The comparison results are presented in Table 5.2. The simulation results show that the deviations between the physical and simulated production scenarios are lower than one percent. However, a comprehensive comparison of the physical and the digital model is missing for this research because the physical Learning Factory 4.0 is not able to produce long production schedules without technical issues (e.g., breakdown of machines, WiFi connection issues). Therefore, it was assumed that random production programs can adequately be simulated.

Table 5.2: Comparison of the physical and simulated Learning Factory 4.0.

	Physical System		Simulation Model	
	Average Lead Time [mm:ss]	**Total Energy Demand [Wh]**	**Average Lead Time [mm:ss]**	**Total Energy Demand [Wh]**
White Products	05:25.8	22.18	05:24.1 (-0.52 %)	22.17 (-0.06 %)
Red Products	04:57.9	10.22	05:00.3(+0.82 %)	10.15 (-0.47 %)
Blue Products	05:13.3	10.55	05:12.2 (-0.35 %)	10.47 (-0.89 %)

Moreover, the simulation model was extended by additional processes enabling sustainable manufacturing: renewable energy use, disposal or reuse of materials, and worker fatigue.

The renewable energy demand was modeled as a function that balances the available renewable energy and the energy demand of the production system. The available renewable energy was simulated using real renewable energy generation data from the local renewable energy plant of the University of Applied Life Sciences Emden (Hochschule Emden/Leer).

The disposal or reuse of materials was modeled through an additional workstation (see Figure 5.4). The carriers were reused, using a probability of 30%. The probability was an AnyLogic® function for the random material flow.

The worker fatigue was modeled in an additional workstation for the material preparation (see Figure 5.4). In general, worker fatigue can be modeled based on attributes like heart rate (La Riva et al., 2015), energy expenditure (Garg et al., 1978), and muscular exhaustion (Jaber and Neumann, 2010). Regardless of the fatigue´s nature, the models use exponential (El Mouayni et al., 2020) and linear functions (Soo et al., 2009). However, no consensus exists for several reasons. The modeling depends on how 'fatigue' is operationalized and at which level, from the whole body to biochemical reactions, the fatigue phenomenon is considered (Jaber and Neumann, 2010). For the initial modeling efforts presented in the simulation, it was assumed that the fatigue (F) changed linearly over time (see Equation 5.1). The fatigue increase or decrease depended on the worker's status represented by the binary variables w and r:

- If the worker is working, then w = 1 and r = 0.
- If the worker breaks or waits, then w = 0 and r = 1.

The fatigue was determined using data for work intensity (I) and a recovery factor (m) from (Koether et al., 2010), and recovery times (t) were calculated by the simulation model.

$$F\ [kJ] = w * I * t_w - r * I * t_r^m = w * \left(1250\ \frac{kJ}{h} * t_w\ [h]\right) - r * (1250\ \frac{kJ}{h} * t_r\ [h]^{-0.55281}) \qquad \mathbf{5.1}$$

5.1.3 Goals and System Boundaries for Sustainability-Based Production Planning

Table 5.3 presents the specific planning production and sustainability goals and related variables (μ_S and μ_F) for the experimental study. The production and sustainability goals were defined based on the literature review results for commonly used sustainability goals and variables (see Section 4.2). The production goal was limited to the production output. It was assumed that all delivery dates were met for the manufactured products. Therefore, typical planning goals for the processing time were not considered. The sustainability goals considered different sustainability aspects that saved natural resources (1), lowered production costs (2), and avoided social impacts (3).

Table 5.3: Production planning goals and variables for the experimental study.

Production Goal	**Potential to improve the sustainability of the production program**
Total Product Output Rate • White Product Output [products/hour] • Red Product Output [products/hour] • Blue Product Output [products/hour]	**1. Use of Renewable Energy Potential:** • $\mu_{S,1}$: Renewable Energy Utilization [Wh] • $\mu_{F,1}$: Average Queue Time at Resources [seconds/product] **2. Use of Reused Carrier Potential:** • $\mu_{S,2}$: Total Reused Carriers [carriers/hour] • $\mu_{F,2}$: Total Product Output Rate [products/hour] **3. Reduction of Human Stress Potential:** • $\mu_{S,3}$: Accumulated Work Load Peak [kJ] • $\mu_{F,3}$: Average Queue Time Warehouse [seconds/product]

Based on the production and sustainability planning goals, Figure 5.6 presents the system boundaries of Learning Factory 4.0, collecting the required data for the experimental study. For this approach, the system boundaries presented relevant functional units and material flows for the experimental study. The system boundaries bordered the relevant functional units and material flows for the experimental study. Moreover, the system boundaries were the basis for the decision behavior improving the sustainability of the considered production program. The functional unit production process, renewable energy plant, carrier reuse process, and material preparation offered different framework conditions for the sustainability states, which were evaluated with generally accepted sustainability rules (see Section 4.3.4).

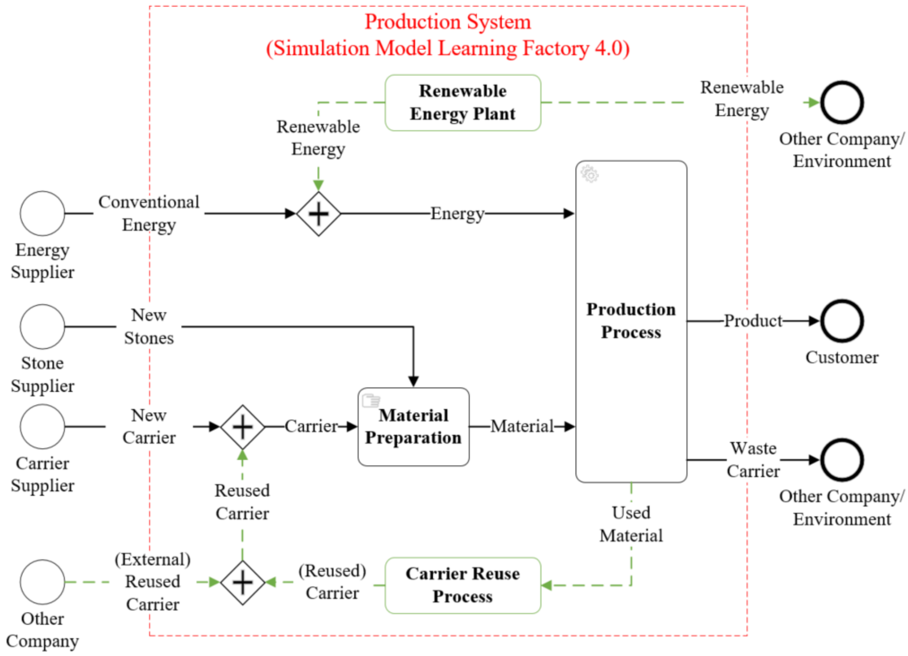


Figure 5.6: System boundaries for the experimental study.

The functional unit **production system** contains the warehouse, four workstations, one transporter, and quality control. With the aid of these production modules, the prepared materials and energy is transformed into finished products. The transformation process is fully automatic and requires no workforce. However, the production systems offer different opportunities to affect the state production flexibility (μ_F): production utilization and queue times. The required production utilization depends on the production output goal and can be controlled through the material release at the warehouse. However, if the production output goal is lower than the maximal possible product output, the production system offers production flexibility. For example, the production utilization can be increased in times of high material availability or decreased in times of limited material. Moreover, the warehouse and four workstations are able to store a semi-finished product in a queue zone. The queue time in these zones can be used to shift the start time of production activities. For example, a semi-finished product has a five-minute queue time after a production activity at workstation one. In this case, the start time of the production activity can be shifted within these five minutes. If the production schedule offers no queue times at the resources, queue times can manually be increased in the schedule.

The functional unit **renewable energy plant** produces renewable energy for the production process. The renewable energy generation depends on weather conditions and cannot be controlled. Therefore, different cases for renewable energy supply exist that have different sustainability effects:

- If the renewable energy generation is equal to the energy demand, no renewable energy is sold to other companies;
- If the renewable energy generation is higher than the energy demand, the production program can be changed to increase the renewable energy demand, renewable energy can be stored, or renewable energy can be sold to other companies;
- If the renewable energy generation is lower than the energy demand, the production program can be changed to decrease the energy demand, or energy needs can be purchased from an external energy supplier, which causes higher energy costs and (in the case of conventional energy) indirect GHG emissions. Therefore, the energy demand should be reduced as long as it is economically possible; and
- If the production flexibility is too low for increasing the renewable energy demand, the queue times must manually be increased in the schedule through shifting the start times of production activities.

The functional unit **carrier reuse** transforms the used carrier from the production process into a reused carrier for the material preparation process. Not all carriers can be reused for the material preparation process (waste carrier), and external carriers must be purchased. Therefore, the following cases affect the sustainability state of the production system:

- Reused carriers can be purchased from other companies, which avoids the usage of new carriers and additional production costs;
- If reused carriers from other companies are not available, new carriers are purchased from an external supplier, which causes higher material costs and impacts natural resources. Therefore, internal or external reused carriers should always be preferred for material preparation; and
- If the production flexibility is too low for increasing the carrier reuse, the production utilization must be decreased through shifting the start times of new production orders.

The functional unit **material preparation** transforms new colored wooden blocks and carriers into material for production. The material preparation is manual work and causes physical stress on the worker. High workload peaks should be avoided to decrease the risk of health impacts on workers.

Therefore, the following actions can be planned to affect the sustainability state of the production system:

- Production activities can be shifted at times with a low workload for the material preparation process;
- Additional breaks can be planned to reduce the workload for the worker;
- Additional workforce can be scheduled for the material preparation; and
- If the production flexibility is too low for decreasing the workload, queue times at the warehouse must manually be increased in the schedule through shifting the start times of new material releases.

Based on the system boundaries, the production system of the Learning Factory 4.0 was analyzed to get a basic understanding of the system behavior. For this approach, Monte Carlo simulation experiments were used to collect data. In general, a Monte Carlo simulation experiment analyzes a random distribution of a model output, simulating the same model input multiple times (Metropolis et al., 1953). The following production data were collected and analyzed: maximal production output, average product lead time, total energy demand, carrier reuse rate, and maximal workload. The maximal product output was determined by simulating different material release times. The minimal release time interval lead to a maximal utilization of the bottleneck resource (Transporter). Therefore, lower release interval times did not affect the total production output. The following reference production scenarios were defined and simulated:

- Production of only White Product
- Production of only Red Product
- Production of only Blue Product
- Production of a Product Mix (Red/White/Blue)

Table 5.4 presents simulation results for the reference scenarios analyzing 1,000 simulation runs. The distribution is represented as the average value and standard deviation.

Table 5.4: Average production data and standard deviation of the reference scenarios.

	Product White	Product Red	Product Blue	Product Mix Red/ White/ Blue
Minimal Material Release Interval [mm:ss]	02:45	02:30	02:30	02:30
Maximal Product Output [Products/hour]	20.78 (0)	22.67 (0)	22.44 (0)	7.33 (0)/ 7.22(0)/ 7.22 (0)
Average Product Lead Time [mm:ss]	05:28.6 (0.13)	05:07.0 (0.03)	05:20.6 (0.02)	08:41.6 (0.40)/ 07:05.6 (0.40)/ 07:57.1 (0.46)
Energy Demand [Wh]	73.00 (0.04)	77.87 (0.03)	77.34 (0.01)	75.77 (0.03)
Carrier Reuse Rate [Carrier/Product]	0.30 (0.03)	0.30 (0.03)	0.30 (0.03)	0.30 (0.03)
Maximum Work Load Peak [kJ]	1,371 (4)	1,521 (4)	1,521 (4)	1,521 (4)
Average Queue Time [Seconds/Product]	36.86 (0.12)	33.61 (0.04)	35.60 (0.03)	65.78 (0.09)

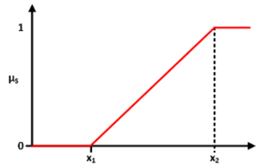
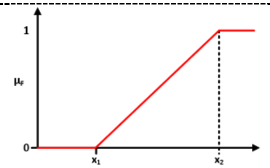
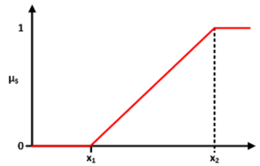
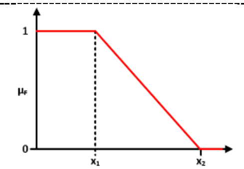
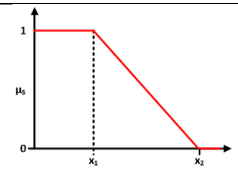
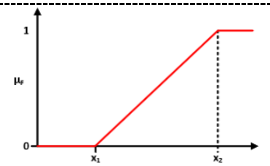
5.2 Fuzzy Set Configuration

Based on the defined sustainability goals, system boundaries, and reference scenarios above, the learning factory production processes were analyzed to collect required data for the fuzzy sets. As mentioned in Section 4.2., fuzzy sets analyze variables between the most and the least desirable values using membership functions to determine the state of sustainability and production flexibility.

For this approach, Table 5.5 presents the shape of the membership functions, description of the fuzzy set values, and final membership functions for the considered production system. The following method and sources were used to determine the fuzzy set values (x_1 and x_2):

- The fuzzy value ranges for renewable utilization ($\mu_{S,1}$), average queue time production program ($\mu_{F,1}$), and average queue time warehouse ($\mu_{F,3}$) were determined with sensitivity analysis simulation experiments.
- The fuzzy values for reuse of carriers ($\mu_{S,2}$) and production output ($\mu_{F,2}$) were determined based on the production planner's experience and production system knowledge.
- The fuzzy value for the work intensity ($\mu_{S,3}$) was determined based on external empirical data.

Table 5.5: Overview of fuzzy sets for the experimental study.

Variable	Membership function Shape	Description Value x_1	Description Value x_2	Membership Function
Renewable Energy Usage (REU)	S,1 	Minimally acceptable renewable energy utilization for the production process [%]. In this case, x_1=0.84.	Best case of renewable energy utilization for the production process [%]. In this case, x_2=0.98.	$\mu_{S,1} = \begin{cases} 0, & x_{REU} \leq 0.84 \\ \frac{x_{REU} - 0.84}{0.98 - 0.84}, & 0.84 < x_{REU} < 0.98 \\ 1, & x_{REU} \geq 0.98 \end{cases}$
Average Production Queue Time (QT_PP)	F,1 	Queue time, which offers no production flexibility [seconds/product]. In this case, x_1=0.	Queue time, which offers high production flexibility [seconds/product]. In this case, x_2=11.	$\mu_{F,1} = \begin{cases} 0, & x_{QT,PP} = 0 \\ \frac{x_{QT,PP}}{11.00}, & 0 < x_{QT,PP} < 11.00 \\ 1, & x_{QR,PP} \geq 11.00 \end{cases}$
Use of Recycled Carrier (CRU)	S,2 	Minimally acceptable reuse of internal and external carriers for the material preparation [%]. In this case, x_1=0.5.	Best case of reuse of internal and external carriers for the material preparation [%]. In this case, x_2=0.9.	$\begin{matrix} 0, & x_{CRU} \leq 0.5 \\ \frac{x_{CRU} - 0.5}{0.9 - 0.5}, & 0.5 < x_{CRU} < 0.9 \\ 1, & x_{CRU} \geq 0.9 \end{matrix}$
Total Product Output (PO)	F,2 	Minimal product output, which offers no flexibility [products/hour]. In this case, x_1=15.	Maximal possible production output [products/hour]. In this case, x_2=20.	$\mu_{F,2} = \begin{cases} 0, & x_{PO} \leq 15 \\ \frac{x_{PO} - 15}{20 - 15}, & 15 < x_{PO} < 20 \\ 1, & x_{PO} \geq 20 \end{cases}$
Accumulated Workload Peak (WL)	S,3 	Low work intensity [kJ]. In this case, x_1=1,000.	Medium workload [kJ]. In this case, x_2=1,250.	$\mu_{S,3} = \begin{cases} 1, & x_{WL} < 1000 \\ \frac{1250 - x_{WL}}{1250 - 1000}, & 1000 < x_{WL} < 1250 \\ 0, & x_{REU} > 1250 \end{cases}$
Average Warehouse Queue Time (QT_WH)	F,3 	Queue time, which offers no production flexibility [seconds/product]. In this case, x_1=0.	Queue time, which offers high production flexibility [seconds/product]. In this case, x_2=20.71.	$\mu_{F,3} = \begin{cases} 0, & x_{QT,WH} = 0 \\ \frac{x_{QT,WH}}{20.71}, & 0 < x_{QT,WH} < 20.71 \\ 1, & x_{QR,WH} > 20.71 \end{cases}$

5.2.1 Renewable Energy Utilization

The fuzzy value range evaluating the renewable utilization ($\mu_{S,1}$) was determined using knowledge generated by sensitivity analysis simulation experiments. In general, a sensitivity analysis is a simulation experiment that determines how output variables are affected based on changes in input variables (Deif, 1986). In this section, the simulation experiment parameters and results for renewable energy utilization and queue time are presented.

The **renewable energy utilization** for a production program was calculated by quoting the total renewable energy demand and total renewable energy generation (see Equation 5.2) (Quachning, 2019).

$$Renewable\ Energy\ Utilization\ (\%) = \frac{Total\ Renewable\ Energy\ Demand\ (Wh)}{Total\ Renewable\ Energy\ Generation\ (Wh)} \cdot 100\% \qquad \textbf{5.2}$$

If the total energy demand of the production system was lower than the renewable generation, the calculation of the renewable energy utilization needed to be adjusted as follows (see Equation 5.3):

$$Renewable\ Energy\ Utilization\ (\%) = \frac{Total\ Renewable\ Energy\ Demand\ (Wh)}{Total\ Energy\ Demand\ (Wh)} \cdot 100\% \qquad \textbf{5.3}$$

The renewable energy generation depends on the renewable energy plant design and the weather conditions. However, the weather conditions could not be controlled and were thus fixed for the sensitivity analysis. Therefore, the renewable energy plant design was varied, and it was assumed that the renewable energy generation was constantly as high as possible. The energy demand depended on the production process and could be controlled through the production utilization of the reference scenarios. However, a full production utilization was simulated, analyzing the highest possible energy demand. Based on these framework conditions, the following sensitivity parameters were set to determine the fuzzy set for the renewable energy utilization variable. The reference scenarios were simulated for a typical working day. The renewable energy plant design varied between 2 and 12 W in 1 W intervals for the single simulation run.

Figure 5.7 presents the results of the sensitivity analysis, which are exemplary for the product mix reference scenario. At 2 W renewable energy generation (see left y-axis), the renewable energy utilization was 100% (see right y-axis). In this case, the renewable energy generation was lower than the minimum energy demand. Therefore, the generated renewable was completely consumed by the production system. Up to a renewable energy generation of 8 W, the renewable energy utilization decreased to 82%. However, the production system was theoretically able to consume more available renewable energy through, for instance, shifting production activities in times of higher renewable energy availability.

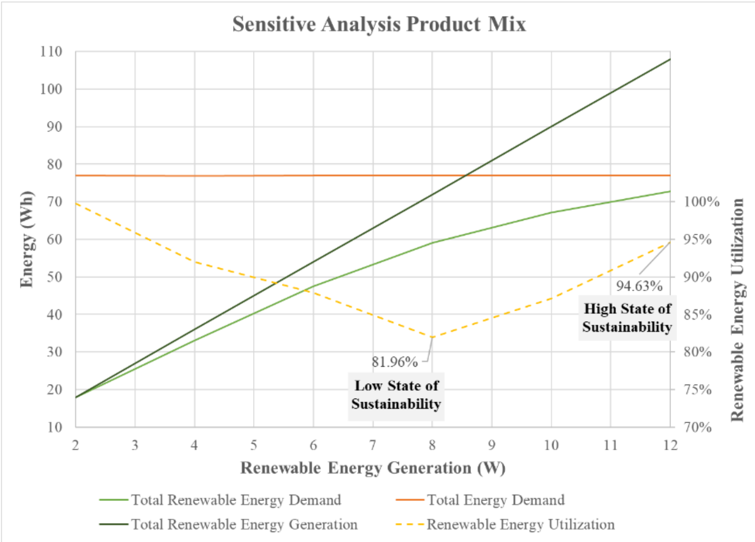


Figure 5.7: Sensitivity analysis results of renewable energy utilization for product mix.

After a renewable energy generation of 8 W, the renewable energy utilization increased because the available renewable energy generation was higher than the total energy demand of the production system.

Figure 5.8 compares the renewable energy utilization of all reference scenarios. For the experimental study, the low state of sustainability was determined by the average of the lowest renewable energy utilizations in the reference scenarios. The high state of sustainability was determined by averaging the renewable utilization at the highest possible renewable energy generation (12 W). The final fuzzy set ($\mu_{S,1}$) is presented in Table 5.5. With the aid of the fuzzy set, random conditions for renewable energy generation and energy demand could be evaluated for sustainability-based production planning.

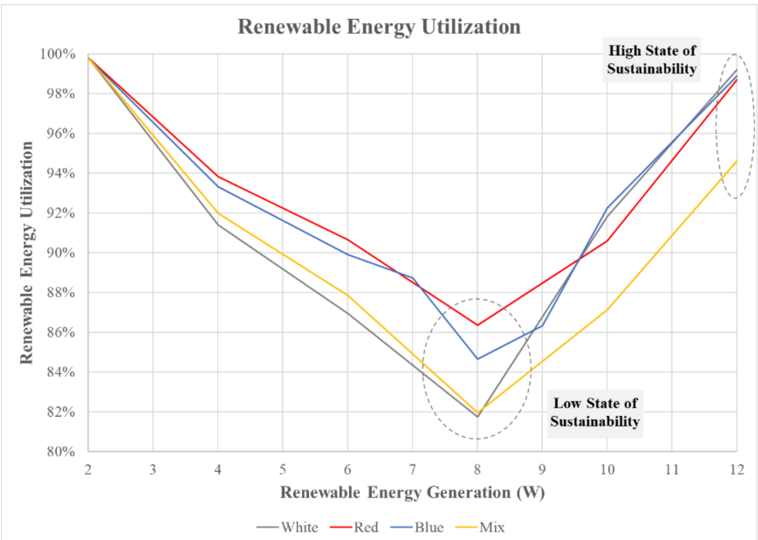


Figure 5.8: Sensitivity analysis results for the renewable energy utilization.

5.2.2 Average Queue Time

The fuzzy value ranges evaluating the average queue time production program ($\mu_{F,1}$) and average queue time warehouse ($\mu_{F,3}$) were determined using knowledge generated by sensitivity analysis simulation experiments.

In general, the **queue time** is defined as the average time of products' operationally induced waiting for the next production step (Schäfer, 1978). The Learning Factory 4.0 contains five resources that offer possible queue zones for the products: warehouse, working station 1, working station 2, working station 3, and working station 4. For these resources, the average queue time was calculated by quoting the total queue time and the total product output (see Equation 5.4). The average queue time calculation was used for a single machine and all possible machines at a time.

$$Average\ Queue\ Time\ (seconds/product) = \frac{Total\ Queue\ Time\ (seconds)}{Total\ Product\ Output\ (products)} \qquad \mathbf{5.4}$$

The queue time depended on the production process and could be controlled through the production utilization of the reference scenarios. Therefore, the reference scenarios were simulated, varying the material input between 10 and 22 products/hour at 1 product/hour intervals for the sensitivity analysis.

Figure 5.9 presents the average queue time of the products in seconds at the warehouse. Up to 12 products per hour, no waiting times arose at the warehouse. Therefore, the production flexibility was low at this product rate. With increasing product output, the waiting time increased to a local maximum. After 16 to 18 products per hour, the average queue time decreased to a local minimum because the time of the material release of the warehouse and transportation to the next free working station was decreasing. Between 19 and 20 products per hour, the material handling between the warehouse and transporter reached an optimal timing state, where released material could directly be transported to the next working station. However, at 21 products per hour, the maximal product output was reached, and the average queue time significantly increased. The high state of production flexibility was determined by averaging the average queue time at the local maximum (16 to 18 products per hour) for the experimental study.

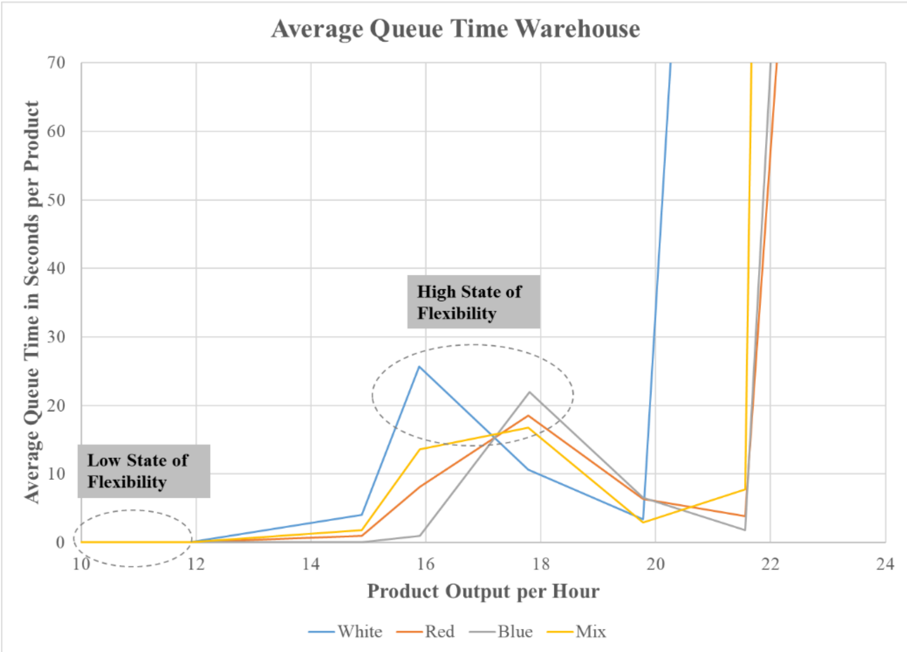


Figure 5.9: Sensitivity analysis results for the queue time at the warehouse.

Figure 5.10 presents the average queue time of the products in seconds for the production program. Similar to Figure 5.9, the average queue time reached local minimum and maximums. The low state of flexibility was determined until 12 products per hour and the high state of flexibility at the first local maximum (20 products per hour). The final fuzzy sets ($\mu_{F,1}$ and $\mu_{F,3}$) are presented in Table 5.5. With the aid of the fuzzy sets, random conditions for the average queue time could be evaluated to determine the production flexibility.

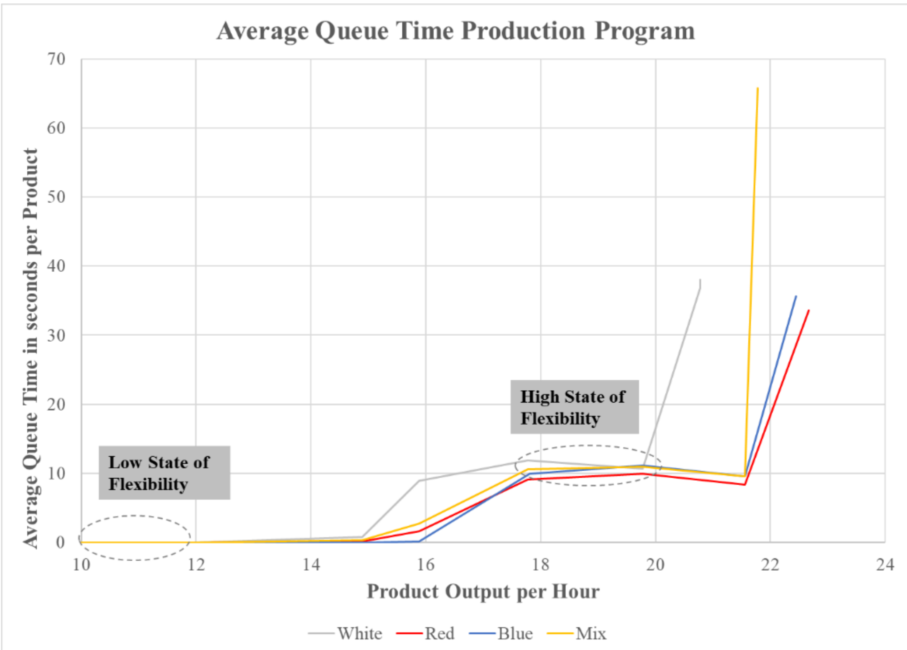


Figure 5.10: Sensitivity analysis results for the queue time for all resources.

5.2.3 Carrier Reuse Ratio and Production Output

The fuzzy value ranges evaluating the carrier reuse ratio ($\mu_{S,2}$) and production output ($\mu_{F,2}$) were determined using system knowledge from the production planner. The carrier reuse ratio was calculated by quoting the numbers for the total reused carriers and total used carriers (see Equation 5.5).

$$Carrier\ Reuse\ Ratio\ (-) = \frac{Total\ Reused\ Carriers\ (Carrier)}{Total\ Used\ Carriers\ (Carrier)} \qquad \mathbf{5.5}$$

For the experimental study, the fuzzy values for the low sustainability state (x_1) were set by 0.75 and by 0.9 for the high sustainability state. The final fuzzy set ($\mu_{S,2}$) is presented in Table 5.5. With the aid of the fuzzy sets, random conditions for the carrier reuse rate could be evaluated to determine the production sustainability. The total production output rate was calculated quoting the numbers for the total product output and total simulation time (Equation 5.6)

$$Total\ Production\ Output\ (Products/hour) = \frac{Total\ Product\ Output\ (Products)}{Total\ Simulation\ Time\ (hour)} \qquad \mathbf{5.6}$$

For the experimental study, the fuzzy values for the low flexibility state (x_1) were set by 15 products per hour and by 20 for the high flexibility state. The final fuzzy sets ($\mu_{F,2}$) are presented in Table 5.5. With the aid of the fuzzy sets, random conditions for the production output could be evaluated to determine the production flexibility.

5.2.4 Workload Peak

The fuzzy value range evaluating the maximal workload peak ($\mu_{S,3}$) was determined using external sources' knowledge (Koether et al., 2010). The maximal workload peak was calculated by determining the maximal occurred workload for a considered planning horizon (see Equation 5.7).

$$Maximal\ Workload\ (kJ) = \max_{0\rightarrow t}[Workload\ (kJ)] \qquad \mathbf{5.7}$$

For the experimental study, the fuzzy value for the high sustainability state (x_1) was set by 1,000 kJ and by 1,250 kJ for the low sustainability state. This workload range corresponded to a medium work intensity (Koether et al., 2010). The final fuzzy sets ($\mu_{S,3}$) are presented in Table 5.5. With the aid of the fuzzy sets, random conditions for the workload peak could be evaluated to determine the production sustainability.

5.3 Proof of Concept of the Decision Support System

In general, a proof of concept is a presentation of the proposed model and its feasibility. The concept proof aims to describe the idea and proposed functionality of the model, including its general design and specific features. The description contains a small-scale implementation of the model to verify its potential (VDI 2221, 1993). For this proof of concept, an experimental study using a laboratory setup was made, implementing and testing the decision support system in a lab environment. The concept-proof methodology and results are presented in the following subsections for the decision support system for sustainability-based production planning.

5.3.1 Experimental Study Methodology and Simulation Parameter

The FIM and decision-making process were demonstrated by evaluating 27 scenarios that simulated the reference production scenario product mix by different sustainability and production flexibility conditions (see Table 5.6). The scenarios differed in production utilization, renewable energy availability, and external carrier input. The scenarios aimed to analyze the behavior of the decision support system for low, medium, and high sustainability and production flexibility framework conditions.

Table 5.6: Scenarios for proof of concept.

Scenario	Production Utilization	Renewable Energy Availability	External Carrier Availability
S1	Low Utililization	Low Availability	Low Availability
S2	Low Utililization	Low Availability	Medium Availability
S3	Low Utililization	Low Availability	High Availability
S4	Low Utililization	Medium Availability	Low Availability
S5	Low Utililization	Medium Availability	Medium Availability
S6	Low Utililization	Medium Availability	High Availability
S7	Low Utililization	High Availability	Low Availability
S8	Low Utililization	High Availability	Medium Availability
S9	Low Utililization	High Availability	High Availability
S10	Medium Utililization	Low Availability	Low Availability
S11	Medium Utililization	Low Availability	Medium Availability
S12	Medium Utililization	Low Availability	High Availability
S13	Medium Utililization	Medium Availability	Low Availability
S14	Medium Utililization	Medium Availability	Medium Availability
S15	Medium Utililization	Medium Availability	High Availability
S16	Medium Utililization	High Availability	Low Availability
S17	Medium Utililization	High Availability	Medium Availability
S18	Medium Utililization	High Availability	High Availability
S19	High Utililization	Low Availability	Low Availability
S20	High Utililization	Low Availability	Medium Availability
S21	High Utililization	Low Availability	High Availability
S22	High Utililization	Medium Availability	Low Availability
S23	High Utililization	Medium Availability	Medium Availability
S24	High Utililization	Medium Availability	High Availability
S25	High Utililization	High Availability	Low Availability
S26	High Utililization	High Availability	Medium Availability
S27	High Utililization	High Availability	High Availability

The parameters were applied to the following scenarios: production utilization, renewable energy availability, and external carrier availability. The production utilization was controlled through the product output and evaluated at the following states:

- Low utilization: 14.9 [h^{-1}],
- Medium utilization: 17.8 [h^{-1}], and
- High utilization: 21.8 [h^{-1}].

The renewable energy availability depended on weather conditions and could not directly be controlled. For the concept proof, three real renewable energy generation profiles were considered. The profiles represent typical renewable energy generations for a solar plant that produces renewable energy on a winter day (low renewable energy availability), an autumn/spring day (medium renewable energy availability), and a summer day (high renewable energy availability). The data were collected and analyzed from a solar plant at the University of Applied Life Sciences Emden/Leer (Hochschule Emden/Leer). For this approach, the solar data profiles for December 2020, February 2021, and July 2021 were analyzed, representing different seasons in the year. The average renewable energy generation profiles were determined using the 15min time-interval profiles for each day of the month (see Figure 5.11).

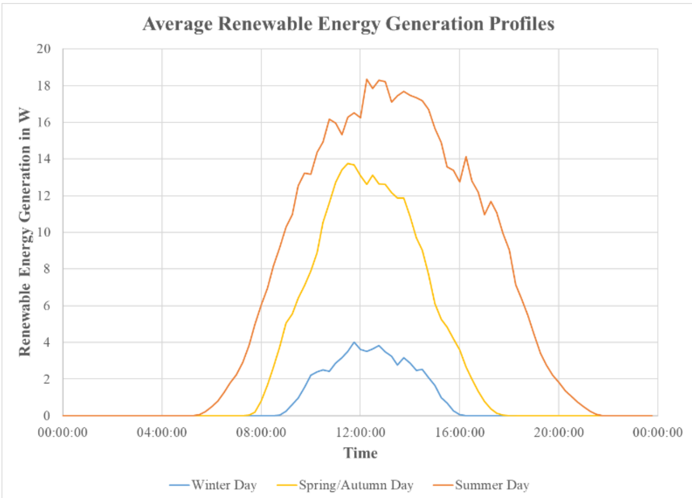


Figure 5.11: Average renewable energy profiles for December and July.

Moreover, the profiles were down-scaled by a factor of 1,000 to fit with the low-energy demands of the Learning Factory 4.0.

The external carrier availability was controlled through the external carrier input rate. The rates were set based on initial simulation experiments varying the external carrier input. The following rates were evaluated for the concept proof:

- Low availability: 4 [h^{-1}],
- Medium availability: 8 [h^{-1}], and
- High availability: 12 [h^{-1}].

Finally, the following basic simulation parameters were set for the Learning Factory 4.0 simulation model:

- It was assumed that the production goal (f) was always fully achieved;
- The accumulated work stress started at zero;
- One iteration step was performed according to the decision-making procedure (see Section 4.3.4) to improve the production program; and
- 1000 Monte Carlo simulations runs were made to determine the average values (and related deviations).

The defuzzification was made using the defuzzification function in Figure 4.11

5.3.2 Experimental Study Results

Figure 5.12 presents an overview of the scenario results for the sustainability improvement potential. Several scenarios had the same or similar results. The scenarios were sorted by increasing sustainability improvement potential (i.e., low to high). This subsection explains the resulting clusters by considering some example scenarios. Moreover, the results are discussed regarding the level of satisfaction with which the FIM outcomes met the expectations.

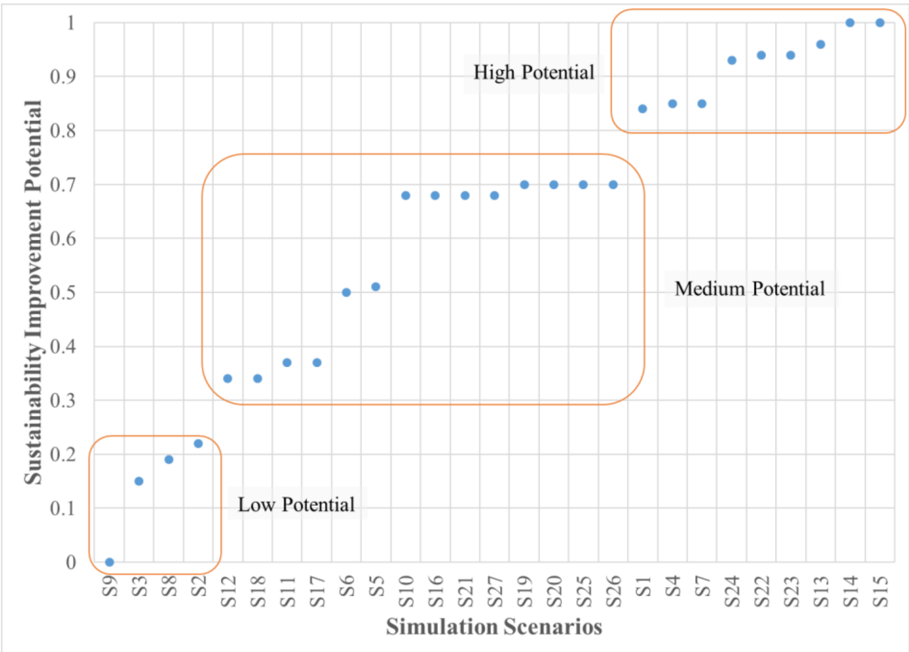


Figure 5.12: Overview scenario results.

The cluster "**low sustainability improvement potential**" indicates that all production goals were achieved, and no actions were required to improve the production program because all sustainability variables demonstrated high sustainability. This result was achieved in four scenarios (see Figure 5.12).

For instance, in scenario 9 (see Table 5.7), the FIM indicates that all sustainability goals were fully achieved ($\mu_{S,1} = \mu_{S,2} = \mu_{S,3} = 1$) due to a low production output but high renewable energy availability and external carrier input. Nevertheless, the FIM outcome shows low production flexibility. Since the sustainability state was as high as possible, the low flexibility did not affect the FIM outcome. Therefore, the FIM offered no recommendations to improve the sustainability of the production program.

Table 5.7: Concept proof scenario results (S9).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	49.72 [Wh]	$\mu_{S,1}$	1	0	0	Potential to improve the production program´s sustainability is low.
QT_PP	0.01 [s]	$\mu_{F,1}$	0			
CRU	14.80 [h^{-1}]	$\mu_{S,2}$	1	0		
PO	14.89 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.07 [s]	$\mu_{F,3}$	0			

For a "**medium sustainability improvement potential**" FIM outcome, production conditions for sustainability ranged between medium and high and between low and medium for production flexibility. These production conditions were simulated in 14 scenarios (see Figure 5.12). Despite a similar classification, the FIM reasoning differed depending on the sustainability state for single sustainability goals. Therefore, two scenarios were selected to explain examples of the medium sustainability improvement potential.

In Scenario 10 (see Table 5.8), the production output was medium, the renewable energy availability low, and the external carrier input medium. Due to these conditions, a medium sustainability improvement potential was indicated ($\mu_{SP} = 0.68$). However, the FIM identified the carrier reuse variable as the main reason ($\mu_{S,2} = 0.05$). Due to the medium production flexibility ($\mu_{F,2} = 0.44$), the simulation model recommended that the production planner increase the carrier reuse process's capacity and/or purchase more external reused carriers from other companies (if possible).

Table 5.8: Concept proof scenario results (S10).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	15.92 [Wh]	$\mu_{S,1}$	0.75	0.24	0.68	Potential to improve the production program´s sustainability is medium
QT_PP	10.11 [s]	$\mu_{F,1}$	0.91			
CRU	9.26 [h-1]	$\mu_{S,2}$	0.05	0.68		
PO	17.78 [h-1]	$\mu_{F,2}$	0.44			
WL	1106 [kJ]	$\mu_{S,3}$	0.57	0.39		
QT_WH	17.54 [s]	$\mu_{F,3}$	0.84			

In Scenario 18 (see Table 5.9), the production output is medium, the renewable energy and external carrier input is high. Due to the medium production output, the medium renewable energy and carrier inputs are enough to supply the production system ($\mu_{S,1}$ = 0.97, $\mu_{S,2}$ = 1). However, the increased production output leads to a higher workload at the material preparation stations ($\mu_{S,3}$ = 0.58), which results in a medium sustainability improvement potential (μ_{SP} = 0.34). Due to the medium production flexibility ($\mu_{F,3}$ = 0.61), the FIM recommended that the production planning increases the breaks between two material preparations and/or increases the workforce at the material preparation station (if possible).

Table 5.9: Concept proof scenario results (S18).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	59.75 [Wh]	$\mu_{S,1}$	0.97	0.03	0.34	Potential to improve the production program´s sustainability is Medium.
QT_PP	11.29 [s]	$\mu_{F,1}$	1			
CRU	16.95 [h^{-1}]	$\mu_{S,2}$	1.00	0.00		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1105 [kJ]	$\mu_{S,3}$	0.58	0.34		
QT_WH	12.56 [s]	$\mu_{F,3}$	0.61			

For a "**high sustainability improvement potential**" FIM outcome, production conditions for sustainability and production flexibility ranged between "Medium" and "High." These production conditions were simulated in nine scenarios (see Figure 5.12). The selected FIM reasoning example related to Scenario 14.

In scenario 14 (see Table 5.10), the production utilization, renewable energy availability, and external carrier input were medium. Due to these conditions, the renewable energy and external carrier were limited; the workload was also high, which resulted in a high improvement potential (μ_{SP} = 1). In this case, the simulation model identified the renewable energy utilization variable as the main contributing factor ($\mu_{S,1}$ = 0). Due to the high production flexibility ($\mu_{F,1}$ = 1), the simulation model recommended that the production planner increase renewable energy utilization by shifting production activities to periods of high renewable energy availability and/or reducing the production output in periods of low renewable energy availability.

Table 5.10: Concept proof scenario results (S14).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	46.23 [Wh]	$\mu_{S,1}$	0	1	1	Potential to improve the production program´s sustainability is high.
QT_PP	11.29 [s]	$\mu_{F,1}$	1			
CRU	13.26 [h^{-1}]	$\mu_{S,2}$	0.59	0.29		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1105 [kJ]	$\mu_{S,3}$	0.58	0.37		
QT_WH	15.16 [s]	$\mu_{F,3}$	0.73			

5.3.3 Experimental Study Result Discussion and Limitations

The experimental study demonstrates that the proposed FIM can determine the sustainability improvement potential for multiple sustainability goals and offers recommendations for improving sustainability. The FIM results were verified by comparing expected results for known sustainability and production flexibility conditions.

For this approach, the FIM was implemented and tested in the Learning Factory Lab of the University of Applied Sciences Emden/Leer. This lab offered ideal framework conditions for testing the FIM in a simulated environment. The FIM and decision-making process was validated by evaluating 27 scenarios that offered known sustainability and production flexibility conditions. Therefore, the FIM implementation and the tests performed were sufficient to reach technology readiness level (TRL) three.

Nevertheless, several limitations were identified for the presented FIM formulation and experimental study. The experimental study was limited to a job shop production system simulating a repetitive production process. Other production types (e.g., batch and flow production) were not considered. Moreover, the experimental study was performed using an experimental setup based on a learning factory lab that offered ideal test conditions. The FIM prototype should be applied in industrial test cases and account for different production types and lot sizes (individual production as well as series production) to reach TRL four and higher.

Besides this, the experimental study was limited to one production goal and three sustainability goals only. Due to limited data provided by the learning factory, testing more goals was not possible. For this approach, a high amount of production data were required to evaluate several production goals (e.g., product forecasts, customer orders, delivery dates) and other sustainability goals (e.g., production waste and effluent, health and safety data of the employees) for comprehensive sustainability evaluation of the learning factory. These data must be connected to the production activities for planning purposes, which was challenging even for a learning factory lab.

Moreover, it was assumed that the production goal for the total product output rate was always achieved and was not adjusted for production planning purposes. In case of low renewable energy availability or carriers, a production output decrease could be one option to achieve the considered sustainability goals. However, a production output decrease could also lead to missed production goals, which would have additional consequences (e.g., non-compliance with delivery dates).

Finally, the decision-making scope was focused on typical production and sustainability processes and neglected management processes for inventory, maintenance, quality control, and product refurbishment and remanufacturing. For this approach, more production data and research are required to implement these processes in the FIM concept for sustainability-based production planning.

5.4 General Implications from the Experimental Study

In general, sustainable system development can only be achieved if the needs and impacts for current and future generations are considered according to the three dimensions of sustainability (Elkington, 1997; WCED, 1987): economic, environmental, and social. Therefore, decision-making models aim to predict and evaluate impacts on current and future systems' sustainability (e.g., financial losses, environmental damages, social issues). However, it has been difficult for enterprises to improve the sustainability of their manufacturing systems. This difficulty is due to different needs, problems, and challenges for sustainable manufacturing. Based on the literature review results and analysis of case studies for production planning, the following general implications were derived from different perspectives (Zarte et al., 2022).

From an organizational perspective, extant approaches for production planning processes usually focus on partial sustainability aspects (economic and/or environmental). The social dimension has been especially neglected in previous research studies. Several reasons for this fact were found in the literature review. Driven by financial markets' expectations, most companies still consider the economic aspect more important than the other two (Hauschild et al., 2017). Moreover, Bhanot et al. (2017) pointed out that one of the main barriers to implementing sustainability practices is the lack of knowledge and the complexity of sustainability (Bhanot et al., 2017). Moreover, the presented literature review shows that the sustainability state of a manufacturing system can only be evaluated indirectly by considering a set of variables (Al-Sharrah et al., 2010; Phillis and Kouikoglou, 2009). The selection of variables and evaluation methods for sustainability depends on the considered system and expert preferences. Moreover, sustainability variables are usually compared against an ideal system state in the form of thresholds or conditions that have been defined as sustainable. This definition is based on knowledge largely stemming from experts, rules for sustainability, or political goals (e.g., SDGs). This lack of general evaluation methods and variable selection criteria is why comparing sustainability study results is impossible. Therefore, new technologies and practices for sustainable manufacturing require clear and transparent communication regarding the understanding (definition) of sustainability and its goals and related variables. Moreover, uniform selection criteria and methods are required for comparing evaluation results across sustainability studies.

From a technological perspective, digitalization is a key enabler for sustainability-based production planning. Integrating data collection and analysis technologies in existing processes is essential to determining sustainability benefits and impacts in manufacturing processes. However, because of the complexity and lack of knowledge, manufacturing enterprises do not know what and when to measure and how measured data can be connected and analyzed to create new information to meet new management requirements for sustainable development (Kusiak, 2017; Zarte and Pechmann, 2017). Moreover, the experimental study illustrated how much data are required to predict a production system's future sustainability state for at least three sustainability goals. For example, collected energy demand needs to be statistically analyzed and correlated for single production activities, producing specific products. Then, the determined energy demand profiles need to be connected with future production programs to predict the required energy demand. The same procedure must be repeated for different sustainability goals, which produce a high amount of data. Therefore, virtualization and cloud-based services are required to plan and control manufacturing operations (Babiceanu and Seker, 2016). Nevertheless, technical and organizational challenges related to reusing data and information must be understood to ensure that new technologies meet data requirements for sustainability-based production planning. Moreover, the author suggests a focused procedure of applying sustainability goals in production planning. The implemented planning system should consider the most relevant sustainability aspects in the production system only, where the sustainability impact of decision-making is most beneficial.

From a human perspective, one of the most important criticisms for the previous three industrial revolutions and their associated policies is the failure to solve the most pressing issues that continue to plague modern societies. These include climate change, chronic diseases, and inequality. With the transition to Industry 4.0, policy- and decision-makers should rethink their behaviors and considering their global impacts on current and future human generations. Society at large should benefit from such industrial transformation, as consumers and producers are largely connected, and both can participate in the production and consumption process (Morrar and Arman, 2017). Moreover, an important part of this transformation to

Industry 4.0 is the emphasis on being human-centred. A human-centred design allows a paradigm shift from independent, automated, and human activities to a human-automation symbiosis characterized by the cooperation of machines with humans in work systems designed not to replace the skills and abilities of humans but rather to co-exist with and help them become more efficient and effective (Romero-Silva et al., 2015; Zarte et al., 2020a). To achieve this, it is imperative to know individuals' behaviors and interests in the various production planning processes. The knowledge of what they do, where they do it, and how they do it needs to be clearly understood to identify sustainability impacts on these individuals in manufacturing systems.

6

Validation of the Research Results

Finally, the research design and results needed to be validated. For this approach, a validation procedure and criteria were selected (see Section 6.1). Then, the procedure and validation criteria were applied to validate the research design, methodology, and results (see Section 6.2).

6.1 Validation Procedure and Criteria

In general, a validation process aims to determine the model accurately compared to the observed phenomenon or behavior of the system (Aumann, 2007). Model validity can be evaluated as follows (Sargent, 1984):

- Operationally by determining if model behavior agrees with observed system behavior using independent data; and
- Conceptually by determining whether the model's theory and assumptions are reasonable using logical deductive reasoning.

Operational model validation requires independent data from the considered system or phenomenon. However, systems and phenomena exist that offer no independent data validating a model (Grunwald, 2013), e.g., climate change models. Climate change models aim to predict the future climate and its effect on the economy in the following decades. However, there is no data for future climate change and its effect. Therefore, operational validation is hardly possible. Sustainability models have similar goals as well as issues.

In general, sustainable system development can only be achieved if the needs and impacts for current and future generations are considered according to the three pillars of sustainability: economic, environmental, and social (Elkington, 1997; WCED, 1987). Therefore, sustainability evaluation models aim to predict and evaluate impacts on a system's sustainability, e.g., financial losses, environmental damages, social issues. However, the system's sustainability cannot be determined as an objective value, and common operational validation procedures cannot be applied for the following reasons.

The main reason is that there is no tool or method for the objective analysis of the system´s sustainability. The sustainability state of a system (e.g., household, enterprise, world) can only be evaluated indirectly by considering a set of variables (Al-Sharrah et al., 2010; Phillis and Kouikoglou, 2009). The selection of variables and evaluation method for sustainability depends on the considered system and expert preferences (see literature review results in Section 3.2). Sustainability variables are usually compared against an ideal system state in the form of thresholds or conditions that have been defined as sustainable. This definition is made according to knowledge stemming from experts, rules for sustainability, or political goals (e.g., SDGs). Moreover, a system is sustainable for a limited timeframe only (see Section 3.1.1). The ideal sustainable system needs to be adapted continuously according to the current system's state of sustainability and new knowledge, rules, and goals. Since there is no general standard or method for defining the ideal sustainability state, a logical deduction of sustainability is not possible, and systems' sustainability can be assessed differently by scientists. However, the selected variables for sustainability assessments themselves can operationally be validated. For example, the simulation model of the Learning Factory 4.0 can be validated. For this approach, product lead times and total energy demand of the simulation model and the physical Learning Factory 4.0 were compared (see Section 5.1.2). However, the research was focused on developing an inference model for sustainability, and, therefore, a more detailed validation of the simulation model was not purposeful.

Another reason is that scientists and experts are part of the sustainable development progress. The communication of sustainability evaluation results and improvements is a scientific statement but also an intervention in future decision-making processes affecting the future sustainability state. Through, for instance, warnings by the Club of Rome (Meadows, 1974) and climate reports by the IPCC (Masson-Delmotte et al., 2018), systems are influenced by these communications. This effect is also known as the "self-destroying prophecy," where a prediction prevents what it predicts from happening (Merton, 1948).

However, conceptual model validation is always feasible, regardless of the type of model. For this approach, several qualitative criteria exist and need to be adapted according to the scientific work (Flick, 2010; Mayring, 1999; Steinke, 2017).

The following qualitative criteria were chosen for the validation process of this research:

- Intersubjective plausibility through documentation of the scientific work;
- Reasoning of the research process;
- Empirical support of the research process through case studies; and
- Limitations of the research work and results.

6.2 Conceptual Validation Results

The research aimed to develop and realize a decision support system for production planning processes that consider sustainability aspects (economic, environmental, and social). For this approach, the following RQs were initially proposed:

RQ 1. How can production systems be evaluated considering all three sustainability dimensions (economic, environmental, and social) for production planning purposes?

RQ 2. What additional information needs to be collected for decision-making in sustainability-based production planning processes?

RQ 3. How can a decision support system use these data and this information to evaluate and improve the sustainability of the production system with the aid of production planning?

The research goal and questions were conceptually validated according to the criteria above in the following subsections.

6.2.1 Intersubjective Plausibility

The criterion "intersubjective plausibility" explains how research results are reached through a reasonable structured documentation. The documentation should contain information about the basic understanding from the researcher for the research topic, reasoning for selecting methods to develop the concept, and the source and collection method of data proofing the concept (Mayring, 1999; Steinke, 2017).

In general, no standard definition exists for sustainability, and researchers always need to define what is meant by sustainability in their presented research contributions. The presented scientific work requires a basic definition for sustainability-based production planning. The deduction of this basic definition for this research was reached through narrative literature reviews (see Section 3.1), with the achieved definition being "the planning of production activities to achieve conventional (economic) production goals, ensuring the enterprises´ operation. Moreover, additional sustainability goals must be achieved, avoiding, reducing, or compensating environmental damages and social issues."

Based on this definition, a systematic literature review was conducted to identify common methods and variables for decision-making in production planning processes while simultaneously considering all three sustainability dimensions (economic, environmental, and social). The literature review revealed several methods and variables for sustainability-based strategic production management, but few examples exist for operational production planning. Extant operational production planning approaches only focus on single sustainability aspects (see Section 3.2). The literature review also showed that fuzzy logic is used in several decision-making approaches. Therefore, fuzzy logic was chosen to develop the inference model for the decision support system for sustainability-based production planning. Next, an additional systematic literature review was conducted to gain an overview and understanding of fuzzy decision-making approaches for sustainable manufacturing (see Section 3.3). The review identified research gaps and limitations of the existing approaches.

Based on this state-of-the-art framework, the decision support system concept for sustainability-based production planning was developed. The concept consisted of four main components. First, the concept contained a general description of the context and scope for the decision-making process (see Section 4.1). The context and scope were based on the common SoS approach, which was also used to describe the basic understanding of sustainability. Second, a systematic literature review was performed that analyzed widely used planning goals and variables for sustainability-based production planning considering all three sustainability dimensions (see Section 4.2). Third, the concept contained a general description for an FIM evaluating the found variables for production planning (see Section 4.3). Finally, a user interface example was designed for sustainability-based production planning, presenting the FIM results and additional data for the production scheduler (see Section 4.4).

The concept was proven through an experimental study using data from a simulation model of the Learning Factory 4.0 located in the University of Applied Life Sciences Emden/Leer. In general, the Learning Factory 4.0 has been developed as a demonstrator for production management and an experimental setup for technical projects. The experimental setup provides data and information that have already been used for different purposes, such as predictive maintenance (Zarte et al., 2017), energy management (Zarte and Pechmann, 2020), and generic simulation modeling (Kassen et al., 2021).

The relevant features of the Learning Factory 4.0 and the experimental study scope were presented in Section 5.1. The FIM was configured based on this scope. For this approach, Monte Carlo and sensitivity analysis simulation experiments were performed to analyze the production processes (see Section 5.2). The behavior of the FIM was tested and verified in 27 production scenarios using low, medium, and high sustainability and production flexibility framework conditions (see Section 5.3). Finally, general implications for sustainability-based production planning were defined based on the experimental study results and experience.

6.2.2 Reasoning

The criterion "reasoning of the research process" concerns how suitable the research design and selected methods are for achieving a research goal. The reasoning is described by arguing the selected methods and publication strategy and presenting the research results to an external scientific audience (Mayring, 1999; Steinke, 2017).

As mentioned above, this research aimed to develop and realize a decision support system for sustainability-based production planning. For this approach, the research methodology (see Section 2) was adapted from the standard for the human-centered design of computer-based interactive systems (ISO 9241-210:2010). The standard provided an iterative procedure and basic principles for the design and test process.

Following this methodology, the decision support system development process reached several stages, which can be categorized by the concept of technology readiness level (TRL).[2] Table 6.1 presents the TRLs proposed by the European Commission to evaluate research project results and progress (European Commission, 2014).

Table 6.1: Description of TRLs for technical projects (European Commission, 2014).

Phase	TRL Level	Description
Research	TRL 1	Basic principles observed.
	TRL 2	Technology concept formulated.
	TRL 3	Experimental proof of concept.
Development	TRL 4	Technology validated in lab.
	TRL 5	Technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies).
	TRL 6	Technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies).
Deployment	TRL 7	System prototype demonstration in an operational environment.
	TRL 8	System complete and qualified.
	TRL 9	Actual system proven in an operational environment (competitive manufacturing in the case of key enabling technologies).

TRLs 1–3 are usually reached in academic research projects. Higher TRLs are reached with the aid of industry support, developing a complete functioning product or service. A

[2] Originally, the TRLs were developed and standardized by NASA for space technologies (ISO Space systems and operations). The TRLs assess the progress of technologies in different phases (research, development, and deployment) and related sub-phases. The sub-phases are presented on a scale of one to nine, where TRL 1 describes a theoretical technology and TRL 9 a complete product. The EU adapted the TRL concept to evaluate the progress and results of technical research projects.

technology can only reach a specific TRL if all requirements and criteria are achieved for that level.

For **TRL 1**, the basic principles and knowledge for the decision support system need to be identified and documented. For this approach, this research methodology started with a planning phase to define the framework conditions (problem statement, motivation, initial RQs) for future research work. Based on the framework conditions, the required scientific knowledge was collected and analyzed by narrative and systematic literature reviews in the second phase of the research methodology. The literature reviews were documented in this thesis and presented to academic audiences through scientific publications (Zarte et al., 2020a, 2019a, 2018a) to reach TRL 1.

For **TRL 2**, the decision support system concept needs to be formulated and documented. The concept was developed in the third and fourth phase of the research methodology and was structured in four parts: (1) the general decision-making scope, (2) the collection of sustainability goals and variables for production planning, (3) the FIM, and (4) the user interface example for sustainability-based production planning. The concept parts were developed using different methods and documented in this thesis and presented to academic audiences through scientific publications to reach TRL 2:

1. The general **decision-making scope** was defined by analyzing influencing factors for sustainability-based production planning (Zarte et al., 2018a) and using the sustainable SoS approach (Zarte et al., 2020b).
2. The **collection of sustainability goals and variables** was also made by literature reviews analyzing existing decision support systems and other approaches for sustainability-based production planning (Zarte et al., 2019c, 2019d). In this part, the Ph.D. RQ 2 was answered, which additional data and information need to be collected for sustainability-based production planning.
3. The **FIM** was documented in two steps. Zarte et al. (2018b) presented the first concept for an FIM to evaluate production programs for short- and mid-term production planning according to sustainability aspects. This concept was further developed in a later paper (Zarte et al., 2021) and fully documented in this Ph.D. thesis. In this part, the Ph.D. RQ of how a decision support system can be used to evaluate the sustainability performance of production programs was answered.

4. The **user interface's** design, prototyping, and usability evaluation followed a user-centred design procedure according to the standard ISO 9241-210:2010. The user interface was designed and tested in three steps. First, a paper prototype was designed and discussed with colleagues and the Ph.D. supervisor. This prototype was not further documented. Second, a digital prototype was created with the aid of the online tool Justinmind and provided the first functionalities to perform simple tasks. The digital prototype was evaluated with the usability test method cognitive walkthrough (Zarte et al., 2019b). The last prototype was applied in an experimental study for sustainability-based production planning and was created with the simulation software AnyLogic®. This prototype is documented in this Ph.D. thesis only.

For **TRL 3**, the developed concept needs to be proven in an appropriate context using laboratory demonstrations, modeling, and simulation. For this approach, the concept was applied to a lab learning factory in the last phases of the methodology. The lab learning factory offered suitable framework conditions for testing the decision support system concept in an ideal environment. The FIM and the user interface were transferred in a simulation model using the software AnyLogic®. The FIM and decision-making process were demonstrated by evaluating 27 scenarios that simulate known production flexibility and sustainability production conditions. The results were presented in scientific papers (Zarte et al., 2022, 2021) and documented in this Ph.D. report to reach TRL 3. In this part, RQ 1 (how can production systems be evaluated considering all three sustainability dimensions (economic, environmental, and social) simultaneously for production planning purposes) was answered. Moreover, general implications for sustainability-based production planning were implicated, identifying needs, problems, and challenges for production schedulers.

For **TRL 4**, a fully functioning prototype of the decision support system needs to be operated in a lab environment, demonstrating, modeling, and simulating key functionalities as integrated software components. This level was not reached in this research because of the following reasons. In TRL 3, the decision support system was realized as a digital model with partial communication possibilities with the physical learning factory. However, the digital model would need to be upgraded to a digital twin that is able to communicate with the physical learning factory. Moreover, the test environment was limited to non-industrial production systems and communication devices, which offered ideal test conditions. TRL 4 requires a non-ideal test environment relative to the final operating environment.

6.2.3 Empirical Support

The “empirical support” criterion describes how the considered system or phenomenon is verified. For this approach, the analytical induction method can be used where a theory or model is tested in single cases or scenarios. If the theory or model cannot explain the considered system or phenomenon, these cases need to be excluded, or the theory or model needs to be redefined (Flick, 2010; Steinke, 2017).

In general, the FIM consists of three steps (see Section 3.3.1): fuzzification, inference, and defuzzification. The FIM outcome depends mainly on the selected fuzzy operator. The fuzzy operator combines fuzzy values for sustainability and production flexibility. For this research's approach, an expected fuzzy output was defined, representing possible sustainability states for a production system. The expected outcome was defined based on the author basic understanding of sustainability and the definition for sustainability-based production planning (see Section 3.1.3). Then, the behavior of the fuzzy operator was tested in two steps.

First, common fuzzy operators were tested in EXCEL based on the defined fuzzy output, combining values for the state of sustainability and production flexibility. The results are presented as a heatmap to compare them with the expected results visually. The comparison shows that common fuzzy operators meet the expected results partially for the FIM only. Therefore, a customized fuzzy function was derived to represent the expected model outcome (see Section 4.3.2).

Second, the customized fuzzy function was tested in an experimental study. For this approach, 27 scenarios were defined to analyze known conditions for sustainability and production flexibility. The experimental study procedure and results are presented in Section 5.3. In all scenarios, the FIM acted as expected, meeting the criteria for empirical support. However, the experimental study was limited to an ideal test case under lab conditions. Therefore, it could not be entirely determined that the model would act as expected in other cases.

6.2.4 Limitations

The criterion "limitation" considers the question of how general the research results are. Different conditions need to be defined for this approach, discussing their application to the presented concept and concept proof (Steinke, 2017).

Section 3.3.2 analyzed existing FIMs, identifying research gaps and limitations. Extant FIMs for strategic enterprise planning cannot be directly adapted for operative production planning. Moreover, these models are applicable to specific products and processes and consider single sustainability aspects for production planning only. These limitations were resolved in the proposed concept for a decision support system for sustainability-based production planning. The concepts presented an FIM for operative production planning that combined variables for all three sustainability aspects (economic, environmental and social).

Moreover, suitable variables commonly used for sustainability-based production planning were collected. The proposed FIM concept could easily be adapted for different types of variables (see Section 4.3.1). The concept requires only that the variables are defined according to specific criteria (see Section 4.1.3); for example, the variables should be related to a sustainability goal, or all selected variables need to be independent of one another.

However, limitations were identified in the presented research, offering opportunities for future work:

- The experimental study was limited to a job shop production system simulating repetitive production. Other production types (e.g., batch and flow production) were not considered. Moreover, the experimental study was performed using a lab learning factory that offered ideal test conditions. The decision support system prototype should be transferred to industry use cases considering different production types and lot sizes (individual production as well as series production);
- The proof of concept was limited to three sustainability variables only. Due to limited data provided by the learning factory, a test of more than three variables was not possible. A high amount of production data are required for a comprehensive sustainability evaluation of production systems. These data need to be connected to different references (e.g., time, production activities, product). For example, previous production programs and collected energy-demand data from machines must be correlated to one another (Kusiak, 2017). The production management system providers identified a lack of data for sustainability-based management processes, and the economic data focus is evolving to emphasize environmental and social data (SAP, 2021). However, this is still an ongoing process;
- The decision-making scope was focused on typical production and sustainability processes and neglected management processes for inventory, maintenance, quality control, and product refurbishment and remanufacturing. Additional research is required to implement these processes in the concept for sustainability-based production planning too;
- The developed FIM applied equal weights of importance for the selected variables. Refinement can be introduced to weigh variables according to their importance or preferences for production planning;
- Finally, the current prototype was realized as a digital model specifically developed for the Learning Factory 4.0. The digital model offered limited interfaces communicating with the physical learning factory or other systems. Additional software development is required to get a new prototype that meets the requirements for TRL 4.

7

CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

Production planning that considers economic, environmental, and social aspects is a complex and challenging task for manufacturing enterprises. Existing approaches for sustainability-based production planning lack a clear definition for the considered system and its sustainability problems. Moreover, the selection of decision-making methods and sustainability goals and variables follows subjective reasoning. The social dimension has been especially neglected in previous approaches for production planning.

Based on these issues, the following RQs were defined for this research:

RQ 1. How can production systems be evaluated considering all three sustainability dimensions (economic, environmental, and social) for production planning purposes?

RQ 2. What additional information needs to be collected for decision-making in sustainability-based production planning processes?

RQ 3. How can a decision support system use these data and information to evaluate and improve the sustainability of the production system with the aid of production planning?

These RQs were answered by the development, implementation, and experimental study of a decision support system for sustainability-based production planning. For this approach, existing decision support systems were reviewed for sustainability-based production planning, analyzing selected decision-making methods and sustainability goals and variables. The review results show that the selection of a decision-making method follows no general guidelines or rules, and no common decision-making method for sustainability-based production planning exists. However, fuzzy logic has been widely used for decision support systems for sustainable manufacturing and was therefore also used in this research to evaluate sustainability goals and variables. The review results also revealed a comprehensive collection of economic, environmental, and social goals and variables commonly used for production planning. The relevance of these goals and variables were evaluated according to their frequency of use in the literature.

Based on the sustainability goals and variables, a fuzzy inference model was developed that was able to simultaneously evaluate economic, environmental, and social variables for production planning purposes. The model outcome indicated the most significant potential to improve the sustainability of the planned production using a knowledge base. Moreover, recommendations were given to the production scheduler for how the planned production must be changed to improve sustainability. For this approach, variables for the sustainability state and the production flexibility were combined using fuzzy operators. The research shows that common fuzzy operators are not applicable for this combination of variables. Therefore, a new customized fuzzy function was derived to evaluate sustainability and production flexibility conditions.

The fuzzy inference model outcome was presented with the aid of a user interface for sustainability-based production planning. The user interface was designed following the user-centred design standard for interactive systems (ISO 9241-210:2010). The user interface's key features were a graphical presentation of the planned production, presentation of the potential to improve the sustainability of the planned production, and the opportunity to adjust the planned production, thus increasing sustainability. The features were evaluated and successfully tested by experts and test users.

Finally, an experimental study tested and verified the decision support system concept for sustainability-based production planning. The Learning Factory 4.0 of the University of Applied Sciences Emden/Leer was used for the experimental study, and this lab already uses an ERP system for conventional production planning. Moreover, the learning factory offered several opportunities for sustainability-based production planning, such as energy plants for the on-site renewable energy supply and processes for the reuse, recycling, or remanufacturing of materials and products. The fuzzy inference model and decision-making process was tested by evaluating 27 production scenarios that simultaneously considered economic, environmental, and social goals and variables. The fuzzy inference model results were verified by comparing the model results with the expected results for the sustainability state and production flexibility of the learning factory. In all scenarios, the fuzzy inference model results met the expected results.

Nevertheless, several limitations were identified for the presented experimental study, such as the case study being limited to a job shop production system simulating a repetitive production process in a lab environment. However, the decision support system implementation and the tests performed were sufficient to reach TRL 3 successfully. In order to reach TRL

4 and higher, the lab prototype should be applied in industrial test cases considering different production types and lot sizes (e.g., individual production and series production). Moreover, it was assumed that the production goal for the total product output rate was always achieved and was thus not adjusted for production planning purposes. In the case of suboptimal sustainability production conditions (e.g., low renewable energy availability), a production output decrease could be one option to achieve the considered sustainability goals. However, a production output decrease could lead to missing the production goals, which has economic consequences (e.g., non-compliance with delivery dates).

Based on the experimental study results and experience performing the experimental study, the following general implications were defined for sustainability-based production planning:

- New technologies and practices for sustainable manufacturing need clear and transparent communication about the definition of sustainability and its problems, goals, and related variables;
- Technical and organizational challenges of reusing data and information need to be understood to ensure that new technologies meet data requirements for sustainability-based production planning;
- A focused procedure of applying sustainability goals in production planning is suggested for considering the most relevant sustainability aspects and where the sustainability impact of decision-making is most beneficial;
- It is important to know and understand individuals' behavior and interests (what they do, where they do it, and how they do it) for those involved in the various production processes to evaluate social aspects in production planning processes.

In the last phase of the research, the research design and results were conceptually validated according to qualitative criteria: intersubjective plausibility, reasoning, empirical support, and limitations. The conceptual validation aimed to reflect on and discuss the research design, methodology, and results. For this approach, the intersubjective plausibility of the research was described, illustrating and arguing the research documentation structure. The reasoning of the research was also presented, specifically the selected methods and tools to answer the RQs. Moreover, the publication strategy was presented, particularly how the research results were or will be published and presented to external scientific audiences. The empirical support was similarly described, outlining the methodology for the experimental study to verify the developed fuzzy inference model for sustainability-based production planning. Finally, the limitations of the research work and results were presented and discussed.

Based on these limitations, this work offers several opportunities for future research. The decision support system prototype should be applied to industrial use cases to reach TRL 4 and higher. For this approach, additional software development is required, especially implementing digital communication interfaces according to industrial standards. Moreover, the experimental study was limited to three sustainability goals only. Additional goals should be implemented to analyze production system's sustainability more comprehensively. Finally, the decision-making scope was focused on typical production processes and ignored management processes for inventory, maintenance, quality control, product refurbishment, and product remanufacturing. Additional research is required to implement these processes in the concept for sustainability-based production planning.

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APPENDIX: OVERVIEW OF THE SIMULATION RESULTS

Production Conditions S1:

- Low production utilization
- Low renewable energy availability
- Low external carrier availability

The expected sustainability potential is high because of low production utilization (-> high production flexibility, $\mu_{F,2} = 1$) and low external carrier availability (-> low sustainability state, $\mu_{S,2} = 0.16$).

Table A.1: Concept proof scenario results (S1).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	15.81 [Wh]	$\mu_{S,1}$	0.70	0.18	0.84	Potential to improve the production program´s sustainability is High.
QT_PP	0.19 [s]	$\mu_{F,1}$	0.02			
CRU	8.43 [h^{-1}]	$\mu_{S,2}$	0.16	0.84		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.72 [s]	$\mu_{F,3}$	0.03			

Production Conditions S2:

- Low production utilization
- Low renewable energy availability
- Medium external carrier availability

The expected sustainability potential is medium because of low production utilization (-> high production flexibility, $\mu_{F,2} = 1$) but medium external carrier availability (-> medium sustainability state, $\mu_{S,2} = 0.81$).

Table A.2: Concept proof scenario results (S2).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	15.81 [Wh]	$\mu_{S,1}$	0.70	0.18	0.19	Potential to improve the production program´s sustainability is Medium.
QT_PP	0.14 [s]	$\mu_{F,1}$	0.01			
CRU	12.35 [h^{-1}]	$\mu_{S,2}$	0.81	0.19		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.72 [s]	$\mu_{F,3}$	0.03			

Production Conditions S3:

- Low production utilization
- Low renewable energy availability
- High external carrier availability

The expected sustainability potential is medium because of low production utilization (-> low production flexibility, $\mu_{F,1} = 0$) and low renewable energy availability (-> medium sustainability state, $\mu_{S,1} = 0.71$).

Table A.3: Concept proof scenario results (S3).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	15.82 [Wh]	$\mu_{S,1}$	0.71	0.15	0.15	Potential to improve the production program´s sustainability is Medium.
QT_PP	0.01 [s]	$\mu_{F,1}$	0			
CRU	14.82 [h^{-1}]	$\mu_{S,2}$	1	0		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.07 [s]	$\mu_{F,3}$	0			

Production Conditions S4:

- Low production utilization
- Medium renewable energy availability
- Low external carrier availability

The expected sustainability potential is high because of low production utilization (-> high production flexibility, $\mu_{F,2} = 1$) and low external carrier availability (-> low sustainability state, $\mu_{S,2} = 0.15$).

Table A.4: Concept proof scenario results (S4).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	40.08 [Wh]	$\mu_{S,1}$	0	0.51	0.85	Potential to improve the production program´s sustainability is High.
QT_PP	0.19 [s]	$\mu_{F,1}$	0.02			
CRU	8.41 [h^{-1}]	$\mu_{S,2}$	0.15	0.85		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	909 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.96 [s]	$\mu_{F,3}$	0.05			

Production Conditions S5:

- Low production utilization
- Medium renewable energy availability
- Medium external carrier availability

The expected sustainability potential is medium because of low production utilization (-> low production flexibility, $\mu_{F,1} = 0.01$) and medium renewable energy carrier availability (-> low sustainability state, $\mu_{S,2} = 0$).

Table A.5: Concept proof scenario results (S5).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	40.08 [Wh]	$\mu_{S,1}$	0	0.51	0.51	Potential to improve the production program´s sustainability is Medium.
QT_PP	0.14 [s]	$\mu_{F,1}$	0.01			
CRU	12.35 [h^{-1}]	$\mu_{S,2}$	0.81	0.19		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.72 [s]	$\mu_{F,3}$	0.03			

Production Conditions S6:

- Low production utilization
- Medium renewable energy availability
- High external carrier availability

The expected sustainability potential is medium because of low production utilization (-> low production flexibility, $\mu_{F,1} = 0.01$) and medium renewable energy carrier availability (-> low sustainability state, $\mu_{S,2} = 0$).

Table A.6: Concept proof scenario results (S6).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	40.11 [Wh]	$\mu_{S,1}$	0.00	0.50	0.50	Potential to improve the production program´s sustainability is Medium.
QT_PP	0.14 [s]	$\mu_{F,1}$	0.01			
CRU	14.80 [h^{-1}]	$\mu_{S,2}$	1	0		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.72 [s]	$\mu_{F,3}$	0.03			

Production Conditions S7:

- Low production utilization
- High renewable energy availability
- Low external carrier availability

The expected sustainability potential is high because of low production utilization (-> high production flexibility, $\mu_{F,2} = 1$) and low external carrier availability (-> low sustainability state, $\mu_{S,2} = 0.15$).

Table A.7: Concept proof scenario results (S7).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	49.72 [Wh]	$\mu_{S,1}$	1	0	0.85	Potential to improve the production program´s sustainability is High.
QT_PP	0.19 [s]	$\mu_{F,1}$	0.02			
CRU	8.41 [h^{-1}]	$\mu_{S,2}$	0.15	0.85		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	909 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.95 [s]	$\mu_{F,3}$	0.05			

Production Conditions S8:

- Low production utilization
- High renewable energy availability
- Medium external carrier availability

The expected sustainability potential is high because of low production utilization (-> high production flexibility, $\mu_{F,2} = 1$) and medium external carrier availability (-> medium sustainability state, $\mu_{S,2} = 0.19$).

Table A.8: Concept proof scenario results (S8).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	49.72 [Wh]	$\mu_{S,1}$	1	0	0.19	Potential to improve the production program´s sustainability is Medium.
QT_PP	0.14 [s]	$\mu_{F,1}$	0.01			
CRU	12.34 [h^{-1}]	$\mu_{S,2}$	0.81	0.19		
PO	14.88 [h^{-1}]	$\mu_{F,2}$	1			
WL	908 [kJ]	$\mu_{S,3}$	1	0		
QT_WH	0.72 [s]	$\mu_{F,3}$	0.03			

Production Conditions S11:

- Medium production utilization
- Low renewable energy availability
- Medium external carrier availability

The expected sustainability potential is medium because of medium production utilization (-> medium production flexibility, $\mu_{F,3} = 0.73$) and medium work workload (-> medium sustainability state, $\mu_{S,3} = 0.58$).

Table A.9: Concept proof scenario results (S11).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	15.92 [Wh]	$\mu_{S,1}$	0.75	0.25	0.37	Potential to improve the production program´s sustainability is Medium.
QT_PP	10.81 [s]	$\mu_{F,1}$	0.98			
CRU	13.27 [h^{-1}]	$\mu_{S,2}$	0.59	0.29		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1106 [kJ]	$\mu_{S,3}$	0.58	0.37		
QT_WH	15.18 [s]	$\mu_{F,3}$	0.73			

Production Conditions S12:

- Medium production utilization
- Low renewable energy availability
- High external carrier availability

The expected sustainability potential is medium because of medium production utilization (-> medium production flexibility, $\mu_{F,3} = 0.61$) and medium work workload (-> medium sustainability state, $\mu_{S,3} = 0.58$).

Table A.10: Concept proof scenario results (S12).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	15.90 [Wh]	$\mu_{S,1}$	0.74	0.26	0.34	Potential to improve the production program´s sustainability is Medium.
QT_PP	11.28 [s]	$\mu_{F,1}$	1			
CRU	16.98 [h^{-1}]	$\mu_{S,2}$	1.00	0.00		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1105 [kJ]	$\mu_{S,3}$	0.58	0.34		
QT_WH	12.60 [s]	$\mu_{F,3}$	0.61			

Production Conditions S13:

- Medium production utilization
- Medium renewable energy availability
- Low external carrier availability

The expected sustainability potential is high because of medium production utilization (-> high production flexibility, $\mu_{F,1} = 0.73$) and medium renewanble energy (-> low sustainability state, $\mu_{S,1} = 0$).

Table A.11: Concept proof scenario results (S13).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	46.20 [Wh]	$\mu_{S,1}$	0	0.96	0.96	Potential to improve the production program´s sustainability is High.
QT_PP	11.10 [s]	$\mu_{F,1}$	0.92			
CRU	9.25 [h^{-1}]	$\mu_{S,2}$	0.05	0.68		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1107 [kJ]	$\mu_{S,3}$	0.57	0.39		
QT_WH	17.56 [s]	$\mu_{F,3}$	0.84			

Production Conditions S15:

- Medium production utilization
- Medium renewable energy availability
- High external carrier availability

The expected sustainability potential is high because of medium production utilization (-> high production flexibility, $\mu_{F,1}$ = 1) and medium renewable energy availiability (-> low sustainability state, $\mu_{S,1}$ = 0).

Table A.12: Concept proof scenario results (S15).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	46.23 [Wh]	$\mu_{S,1}$	0	1	1	Potential to improve the production program´s sustainability is High.
QT_PP	11.29 [s]	$\mu_{F,1}$	1			
CRU	16.98 [h^{-1}]	$\mu_{S,2}$	1.00	0.00		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1105 [kJ]	$\mu_{S,3}$	0.58	0.34		
QT_WH	12.60 [s]	$\mu_{F,3}$	0.61			

Production Conditions S16:

- Medium production utilization
- High renewable energy availability
- Low external carrier availability

The expected sustainability potential is medium because of medium production utilization (-> high production flexibility, $\mu_{F,2}$ = 0.44) and low external carrier availability (-> low sustainability state, $\mu_{S,2}$ = 0.).

Table A.13: Concept proof scenario results (S16).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	59.80 [Wh]	$\mu_{S,1}$	0.98	0.02	0.68	Potential to improve the production program´s sustainability is Medium.
QT_PP	10.11 [s]	$\mu_{F,1}$	0.92			
CRU	9.28 [h^{-1}]	$\mu_{S,2}$	0.06	0.68		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1106 [kJ]	$\mu_{S,3}$	0.57	0.39		
QT_WH	17.58 [s]	$\mu_{F,3}$	0.84			

Production Conditions S17:

- Medium production utilization
- High renewable energy availability
- Medium external carrier availability

The expected sustainability potential is medium because of medium production utilization (-> high production flexibility, $\mu_{F,3} = 0.73$) and medium work workload (-> medium sustainability state, $\mu_{S,3} = 0.58$).

Table A.14: Concept proof scenario results (S17).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	59.80 [Wh]	$\mu_{S,1}$	0.98	0.02	0.37	Potential to improve the production program´s sustainability is Medium.
QT_PP	10.82 [s]	$\mu_{F,1}$	0.98			
CRU	13.29 [h^{-1}]	$\mu_{S,2}$	0.60	0.29		
PO	17.78 [h^{-1}]	$\mu_{F,2}$	0.44			
WL	1106 [kJ]	$\mu_{S,3}$	0.58	0.37		
QT_WH	15.16 [s]	$\mu_{F,3}$	0.73			

Production Conditions S19:

- High production utilization
- Low renewable energy availability
- Low external carrier availability

The expected sustainability potential is medium because of high production utilization (-> medium production flexibility, $\mu_{F,3} = 0.40$) and high work workload (-> low sustainability state, $\mu_{S,3} = 0$).

Table A.15: Concept proof scenario results (S19).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	16.21 [Wh]	$\mu_{S,1}$	0.87	0.12	0.70	Potential to improve the production program´s sustainability is Medium.
QT_PP	9.68 [s]	$\mu_{F,1}$	0.88			
CRU	10.46 [h^{-1}]	$\mu_{S,2}$	0.01	0.49		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1370 [kJ]	$\mu_{S,3}$	0	0.70		
QT_WH	8.20 [s]	$\mu_{F,3}$	0.40			

Production Conditions S20:

- High production utilization
- Low renewable energy availability
- Medium external carrier availability

The expected sustainability potential is medium because of high production utilization (-> medium production flexibility, $\mu_{F,3} = 0.40$) and high work workload (-> low sustainability state, $\mu_{S,3} = 0$).

Table A.16: Concept proof scenario results (S20).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	16.22 [Wh]	$\mu_{S,1}$	0.88	0.12	0.70	Potential to improve the production program´s sustainability is Medium.
QT_PP	9.71 [s]	$\mu_{F,1}$	0.88			
CRU	14.45 [h^{-1}]	$\mu_{S,2}$	0.40	0.30		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1370 [kJ]	$\mu_{S,3}$	0	0.70		
QT_WH	8.37 [s]	$\mu_{F,3}$	0.40			

Production Conditions S21:

- High production utilization
- Low renewable energy availability
- High external carrier availability

The expected sustainability potential is medium because of high production utilization (-> medium production flexibility, $\mu_{F,3} = 0.36$) and high work workload (-> low sustainability state, $\mu_{S,3} = 0$).

Table A.17: Concept proof scenario results (S21).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	16.19 [Wh]	$\mu_{S,1}$	0.86	0.13	0.68	Potential to improve the production program´s sustainability is Medium.
QT_PP	9.51 [s]	$\mu_{F,1}$	0.86			
CRU	18.37 [h^{-1}]	$\mu_{S,2}$	0.85	0.08		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1368 [kJ]	$\mu_{S,3}$	0	0.68		
QT_WH	7.37 [s]	$\mu_{F,3}$	0.36			

Production Conditions S22:

- High production utilization
- Medium renewable energy availability
- Low external carrier availability

The expected sustainability potential is medium because of high production utilization (-> medium production flexibility, $\mu_{F,3}$ = 0.40) and high work workload (-> low sustainability state, $\mu_{S,3}$ = 0).

Table A.18: Concept proof scenario results (S22).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	50.62 [Wh]	$\mu_{S,1}$	0	0.94	0.94	Potential to improve the production program´s sustainability is High.
QT_PP	9.67 [s]	$\mu_{F,1}$	0.87			
CRU	10.42 [h^{-1}]	$\mu_{S,2}$	0.01	0.49		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1370 [kJ]	$\mu_{S,3}$	0	0.70		
QT_WH	8.16 [s]	$\mu_{F,3}$	0.39			

Production Conditions S23:

- High production utilization
- Medium renewable energy availability
- Medium external carrier availability

The expected sustainability potential is high because of high production utilization (-> high production flexibility, $\mu_{F,1}$ = 0.88) and medium renewable energy availiability (-> low sustainability state, $\mu_{S,1}$ = 0).

Table A.19: Concept proof scenario results (S23).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	50.66 [Wh]	$\mu_{S,1}$	0	0.94	0.94	Potential to improve the production program´s sustainability is High.
QT_PP	9.71 [s]	$\mu_{F,1}$	0.88			
CRU	14.43 [h^{-1}]	$\mu_{S,2}$	0.40	0.30		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1369 [kJ]	$\mu_{S,3}$	0	0.70		
QT_WH	8.36 [s]	$\mu_{F,3}$	0.40			

Production Conditions S24:

- High production utilization
- Medium renewable energy availability
- High external carrier availability

The expected sustainability potential is high because of high production utilization (-> high production flexibility, $\mu_{F,1} = 0.86$) and medium renewable energy availiability (-> low sustainability state, $\mu_{S,1} = 0$).

Table A.20: Concept proof scenario results (S24).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	50.66 [Wh]	$\mu_{S,1}$	0	0.93	0.93	Potential to improve the production program´s sustainability is High.
QT_PP	9.50 [s]	$\mu_{F,1}$	0.86			
CRU	18.41 [h^{-1}]	$\mu_{S,2}$	0.85	0.07		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1368 [kJ]	$\mu_{S,3}$	0	0.68		
QT_WH	7.36 [s]	$\mu_{F,3}$	0.36			

Production Conditions S25:

- High production utilization
- High renewable energy availability
- Low external carrier availability

The expected sustainability potential is high because of high production utilization (-> medium production flexibility, $\mu_{F,3} = 0.39$) and high work workload (-> low sustainability state, $\mu_{S,3} = 0$).

Table A.21: Concept proof scenario results (S25).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	70.22 [Wh]	$\mu_{S,1}$	0.72	0.26	0.70	Potential to improve the production program´s sustainability is Medium.
QT_PP	9.67 [s]	$\mu_{F,1}$	0.88			
CRU	10.41 [h^{-1}]	$\mu_{S,2}$	0.01	0.49		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1370 [kJ]	$\mu_{S,3}$	0	0.70		
QT_WH	8.16 [s]	$\mu_{F,3}$	0.39			

Production Conditions S26:

- High production utilization
- High renewable energy availability
- Medium external carrier availability

The expected sustainability potential is high because of high production utilization (-> medium production flexibility, $\mu_{F,3}$ = 0.41) and high work workload (-> low sustainability state, $\mu_{S,3}$ = 0).

Table A.22: Concept proof scenario results (S26).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	70.26 [Wh]	$\mu_{S,1}$	0.73	0.26	0.70	Potential to improve the production program´s sustainability is Medium.
QT_PP	9.72 [s]	$\mu_{F,1}$	0.88			
CRU	14.40 [h^{-1}]	$\mu_{S,2}$	0.40	0.30		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1369 [kJ]	$\mu_{S,3}$	0	0.70		
QT_WH	8.40 [s]	$\mu_{F,3}$	0.41			

Production Conditions S27:

- High production utilization
- High renewable energy availability
- High external carrier availability

The expected sustainability potential is high because of high production utilization (-> medium production flexibility, $\mu_{F,3}$ = 0.35) and high work workload (-> low sustainability state, $\mu_{S,3}$ = 0).

Table A.23: Concept proof scenario results (S27).

Variable	Value	Fuzzy Value		Aggregated Fuzzy Value ($\mu_{SP,j}$)	Aggregated Fuzzy Value (μ_{SP})	Defuzzification (Model Outcome)
REU	70.18 [Wh]	$\mu_{S,1}$	0.72	0.26	0.68	Potential to improve the production program´s sustainability is Medium.
QT_PP	9.50 [s]	$\mu_{F,1}$	0.86			
CRU	18.40 [h^{-1}]	$\mu_{S,2}$	0.85	0.07		
PO	21.56 [h^{-1}]	$\mu_{F,2}$	0			
WL	1368 [kJ]	$\mu_{S,3}$	0	0.68		
QT_WH	7.33 [s]	$\mu_{F,3}$	0.35			

2022

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