SIMONA SKĖRĖ

DECISION SUPPORT METHOD FOR DYNAMIC PRODUCTION PLANNING IN SMALL AND MEDIUM-SIZED COMPANIES

DOCTORAL DISSERTATION

Kaunas
2024

KAUNAS UNIVERSITY OF TECHNOLOGY

SIMONA SKĖRĖ

DECISION SUPPORT METHOD FOR DYNAMIC PRODUCTION PLANNING IN SMALL AND MEDIUM-SIZED COMPANIES

Doctoral dissertation
Technological Sciences, Mechanical Engineering (T 009)

2024, Kaunas

This doctoral dissertation was prepared at Kaunas University of Technology, Faculty of Mechanical Engineering and Design, Department of Production Engineering during the period of 2019–2023.
The doctoral right has been granted to Kaunas University of Technology together with Vytautas Magnus University.

Scientific Supervisor:
Assoc. Prof. Dr. Kazimieras JUZĖNAS (Kaunas University of Technology, Technological Sciences, Mechanical Engineering – T 009).

Edited by: English language editor Dr. Armandas Rumšas (Publishing House *Technologija*), Lithuanian language editor Aurelija Gražina Rukšaitė (Publishing House *Technologija*).

Dissertation Defense Board of Mechanical Engineering Science Field:
Prof. Dr. Saulius BASKUTIS (Kaunas University of Technology, Technological Sciences, Mechanical Engineering, T 009) – **chairperson**;
Prof. Dr. Rimvydas GAIDYS (Kaunas University of Technology, Technological Sciences, Mechanical Engineering, T 009);
Prof. Dr. Juozas PADGURSKAS (Vytautas Magnus University, Technological Sciences, Mechanical Engineering, T 009);
Prof. Dr. Raquel Villena RUIZ (University of Castilla-La Mancha, Spain, Technological Sciences, Electrical and Electronic Engineering, T 001).

The official defense of the dissertation will be held at 10 a.m. on 20 March, 2024 at the public meeting of the Dissertation Defense Board of the Mechanical Engineering Science Field in the Rectorate Hall of Kaunas University of Technology.

Address: K. Donelaičio 73-402, LT-44249, Kaunas, Lithuania.
Phone: (+370) 608 28 527; e-mail doktorantura@ktu.lt

The doctoral dissertation was sent out on 20 of February, 2024.
The doctoral dissertation is available on the internet at http://ktu.edu, at the library of Kaunas University of Technology (Gedimino 50, Kaunas, LT-44239, Lithuania) and at the library of Vytautas Magnus University (K. Donelaičio 52, Kaunas, LT-44244, Lithuania).

KAUNO TECHNOLOGIJOS UNIVERSITETAS

SIMONA SKĖRĖ

SPRENDIMŲ PRIĖMIMO METODAS DINAMINIAM GAMYBOS PLANAVIMUI SMULKAUS IR VIDUTINIO DYDŽIO ĮMONĖSE

Daktaro disertacija
Technologijos mokslai, mechanikos inžinerija (T 009)

2024, Kaunas

Disertacija rengta 2019–2023 metais Kauno technologijos universiteto Mechanikos inžinerijos ir dizaino fakultete, Gamybos inžinerijos katedroje.
Doktorantūros teisė Kauno technologijos universitetui suteikta kartu su Vytauto Didžiojo universitetu.

Mokslinis vadovas:
doc. dr. Kazimieras JUZĖNAS (Kauno technologijos universitetas, technologijos mokslai, mechanikos inžinerija – T 009).

Redagavo: anglų kalbos redaktorius Dr. Armandas Rumšas (leidykla „Technologija“), lietuvių kalbos redaktorė Aurelija Gražina Rukšaitė (leidykla „Technologija“).

Mechanikos inžinerijos mokslo krypties disertacijos gynimo taryba:
prof. dr. Saulius BASKUTIS (Kauno technologijos universitetas, technologijos mokslai, mechanikos inžinerija, T 009) – **pirmininkas**;
prof. dr. Rimvydas GAIDYS (Kauno technologijos universitetas, technologijos mokslai, mechanikos inžinerija, T 009);
prof. dr. Juozas PADGURSKAS (Vytauto Didžiojo universitetas, technologijos mokslai, mechanikos inžinerija, T 009);
prof. dr. Raquel Villena RUIZ (Kastilijos ir La Mančos universitetas, Ispanija, technologijos mokslai, elektros ir elektronikos inžinerija, T 001).

Disertacija bus ginama viešame Mechanikos inžinerijos mokslo krypties disertacijos gynimo tarybos posėdyje 2024 m. kovo 20 d. 10 val. Kauno technologijos universiteto Rektorato salėje.

Adresas: K. Donelaičio g. 73-402, LT-44249 Kaunas, Lietuva.
Tel. (+370) 608 28 527; el. paštas doktorantura@ktu.lt

Disertacija išsiųsta 2024 m. vasario 20 d.
Su disertacija galima susipažinti interneto svetainėje http://ktu.edu, Kauno technologijos universiteto (Gedimino g. 50, Kaunas LT-44239, Lietuva) ir Vytauto Didžiojo universiteto (K. Donelaičio g. 52, Kaunas, LT-44244, Lietuva) bibliotekose.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviations:

AI	Artificial Intelligence;
AM	Additive Manufacturing;
BDA	Big Data Analytics;
CAPP	Computer-Aided Process Planning;
CPs	Cyber-physical systems;
DAQ	Data acquisition system;
DEM	Discrete Element Method;
DMS DPP	Decision support method for dynamic production planning;
DPP	Dynamic production planning;
DSM	Decision support method;
DSS	Decision support system;
DT	Digital Twin;
DTe	Digital Technology;
DTr	Decision Tree;
ERP	Enterprise Resource Planning;
FDM	Finite Difference Method;
FEM	Finite Element Method;
FoT	Factory of Things;
FPY	First Pass Yield;
FRID	Radio-frequency identification;
FVM	Finite Volume Method;
I4.0	Industry 4.0;
I5.0	Industry 5.0;
ICT	Information and communication technologies;
IoT	Internet of Things;
IT-OT	Information technology systems with operational technology systems;
KPIs	Key performance indicators;
MCDA	Multi-criteria decision analysis;
MD	Manufacturing Data;
MES	Manufacturing Execution Systems;
ML	Machine learning;
OEE	Overall Equipment Effectiveness;
OPC UA	Open Platform Communications United Architecture;
ROI	Return of investments;
RTDE	Real-Time Data Exchange;
SIMA	Systems Integration of Manufacturing Applications;
SME	Small and medium-sized enterprise.

INTRODUCTION

The evolution of Industry 4.0 has disrupted the traditional business landscape, necessitating companies to develop systematic plans in order to reduce costs and efficiently scale their operations to meet the market demand. The latest technological advancements offer opportunities to access and analyze data, modernize production facilities, and implement automation and robotization. However, these cutting-edge technologies are not always feasible solutions for SME production companies which often lack the necessary financial resources and knowledge to implement them. Despite their significance in driving the economy, these companies face challenges in keeping pace with modernization due to their reliance on customized production processes and the limited prevalence of automated production methods. They operate in an employee-centered manner, where knowledge, workforce, and decision-making are predominantly human-driven. Given their focus on producing small quantity batches or niche products, these companies engage in dynamic production planning to adapt to the changing requirements throughout the manufacturing process. Factors such as workforce shortages, material and equipment limitations, and uncertainties surrounding new product production can lead to disruptions and a decline in production efficiency. To remain competitive in the market, companies require a user-friendly tool which would provide solutions for real-time production scenarios.

In the light of the aforementioned challenges faced by SMEs in adopting modern technologies, this research aims to address the issue by creating a novel method called the *Decision Support Method for Dynamic Production Planning* (DSM DPP). Unlike the traditional approaches requiring extensive changes in production processes, this method offers a practical solution for enhancing production planning without necessitating significant investments. This method performs production replanning, which involves not only the technical properties of the production site, such as the number of machinery, operations, the power of machinery, etc. but also the main element of an employee-centered enterprise – namely, employees and their skills. This is an important part as Industry 5.0 is now emerging with its human-centricity, sustainability and resilience – the resilience to endure or promptly rebound from difficulties is enhanced when the competencies of employees are taken into account. By implementing DSM DPP, companies can promptly address production interruptions caused by such factors as employee absences, material shortages, machinery failures, or uncertainties in new product operations. This method relies on the availability of quasi-real-time data enabling companies to receive immediate responses and take the appropriate actions to mitigate production stops and optimize their operations. DSM DPP incorporates optimization tasks and simulates physical workspace through several algorithms which have been designed to increase the efficiency of the production process. It is an advanced concept within I4.0 that combines the physical and digital realms to enable enhanced monitoring, analysis, and optimization of processes. Through the integration of these techniques, SMEs can improve their overall production performance and maintain competitiveness in the evolving I4.0 landscape.

In the present research, a mathematical model of DSM DPP is presented. It addresses the optimization task of minimizing the overall process time and maximizing the production profit. The tests were programmed and performed with the *Matlab* program. Through these tests, the research aimed to demonstrate the adaptability and universal applicability of the DSM DPP method across various industries. In order to evaluate the performance of the method, multiple examinations were made by using real data obtained from two companies which are considered as SMEs – a medium-sized metal processing company, and a very small automotive body repair company. These enterprises, which are different in sizes, operations, and the final product, were chosen on purpose to represent diverse production scenarios and challenges commonly encountered by SMEs. The verification involved simulating different production scenarios and assessing the outcomes in terms of the process time and profit. The created method reschedules the overall production plan to perform orders in an efficient sequence by evaluating diverse factors – the skills of employees, the hourly costs of machinery, the energetic outcome, etc.

This method encompasses multiple interdisciplinary domains within the realm of Technological sciences. It begins with production process modelling, which falls under the purview of production engineering, and extends to encompass various branches of mechanical engineering (Fig. 1).

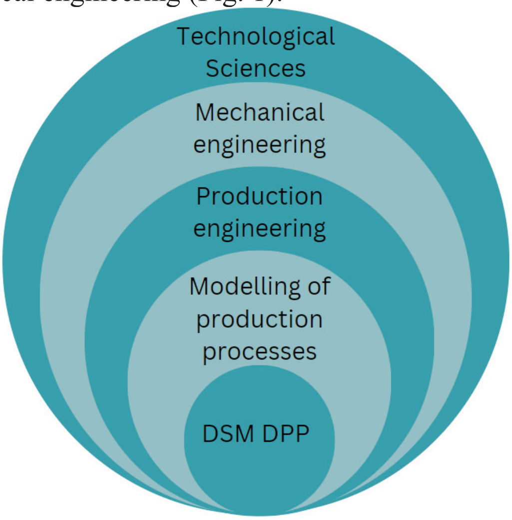


Fig. 1. Positioning of DSM DPP in Technological Sciences

Aim of the work

To create the *Decision Support Method for Dynamic Production Planning* in quasi-real-time to increase the production process efficiency.

Tasks of the dissertation

In order to achieve the above outlined aim of this work, specific tasks were defined:

1. To define the appropriate research methodology in the context of manufacturing engineering at small and medium-sized enterprises.

2. To solve the quasi-real-time production process efficiency optimization problem.
3. To create a computer-aided decision support method for dynamic production planning for small and medium-sized enterprises.
4. To evaluate and prove the appropriateness of the suggested technique by conducting a simulation using real production data.

Scientific novelty

1. The created mathematical optimization function enables to improve the efficiency of production processes in small and medium-sized companies.
2. The developed decision support method for planning dynamic production processes is suitable for production at small and medium-sized enterprises.
3. The created method is intended for employee-centered companies which are a theme in the context of Industry 5.0, while the majority of the available research is still concentrated only on equipment and materials.

Importance of the work

The importance of small and medium-sized enterprises in the overall economy is outstanding, but their limitations to implement the newest technologies in their manufacturing processes and rapid, dynamic production and employee-centered manner shows the need to present an effective but easily adaptable and implemented planning tool. In this study, the issue of dynamic production planning is addressed and solved by the created decision support method for instant replanning of production.

Key statements for defense

1. The created *Decision Support Method for Dynamic Production Planning* increases the efficiency of the production process.
2. The Optimization functions created on the basis of the method ensure time and energy use minimization, along with the maximization of production volumes.

Approbation of the research results

The results of the dissertation have been presented at 5 international and 5 national conferences, published in 4 articles referred in international scientific databases (articles published in journals referred by *ISI Web of Science*), and published in 3 conference proceedings in international scientific databases.

Layout of the dissertation

The dissertation consists of an introduction, 5 sections, and conclusions. The introduction of the dissertation encapsulates the core concepts of the research, its motivation, primary objectives, tasks, originality, significance, and fundamental statements for defense. The dissertation is concluded with a comprehensive list of references; it also provides a list of published works and contributions to conferences.

The page count of the dissertation is 154. There are 89 formulas, 77 figures and 24 tables in the text. The list of references contains 139 entries.

1. REVIEW OF SMEs DYNAMIC PRODUCTION PLANNING METHODS AND ANALYTICS

1.1. Importance of SMEs in Terms of Production

SMEs make up the majority of manufacturing enterprises in the modern production market of the EU [1]. Be it micro, small, or medium enterprises, their role is in the production and sourcing of various products. However, in the light of the technological shift that is bound to come with I4.0, SMEs are not in a favorable position as the technological transformation process poses various barriers due to the nature of how SMEs have been working in the last 30 years.

Technological advancements are propelling the world economy towards a new industrial revolution, driven by innovations, like the IoT, Cloud computing, Big Data, robotics, AI and 3D printing [2]. These transformative technologies offer industries the opportunity to enhance efficiency, improve processes, and create innovative products and services. However, SMEs are facing barriers in adopting digital technologies, particularly in areas like Cloud computing. To overcome these challenges, it is crucial to foster the use of sophisticated digital solutions among SMEs, thereby enabling them to reap the benefits of the digital economy [3].

Technological solutions play a vital role in the evolution of I4.0 and the emerging Industry 5.0 Industry 4.0 focuses on the integration of automation, data exchange, and intelligent systems in manufacturing processes. These solutions enable smart factories, where machines and systems communicate and collaborate autonomously, which leads to an increased efficiency, productivity, and cost savings. I5.0 extends the principles of I4.0, while placing a strong emphasis on collaborative interactions between humans and machines and the integration of human skills with advanced technologies. By combining the capabilities of humans and machines, I5.0 aims to create flexible and personalized manufacturing processes, fostering creativity, innovation, and customization [4].

1.1.1. SMEs in the EU and their importance

SMEs are essential elements of the worldwide economy. They have a significant impact on employment, innovation, and economic growth. Nevertheless, there is no universally agreed-upon definition or originator of this concept. Various countries and regions utilize different criteria, such as the number of employees, the annual turnover, or the industrial branch of a company, to establish their own definitions and classification methods.

According to the latest User Guide to the SME Definition by the European Commission (October 2020), *microenterprises* are those enterprises which employ fewer than 10 people and have an annual turnover or balance sheet total that does not exceed €2 million, whereas *small enterprises* employ fewer than 50 persons and have an annual turnover or balance sheet total that does not exceed €10 million. *Medium-sized enterprises* employ fewer than 250 persons and have an annual turnover that does not exceed €50 million or an annual balance sheet total that does not exceed €43 million [3]. Regardless, despite being small, they make up the majority of EU businesses and cover the majority of the service/goods demand.

In 2021, about 22.8 million SMEs were active in the EU-27, and these SMEs accounted for 99.8% of all enterprises in the non-financial business sector (NFBS) [1], while providing approximately two-thirds of all employment. In terms of production, SMEs often specialize in niche markets or specific product lines, and they can be very agile in responding to changes in demand or market conditions [5]. This flexibility and responsiveness can be especially important in today's rapidly changing business environment, where new technologies and new competitors can emerge at any time.

SMEs are significant employers, especially in developing countries, where they contribute to job creation and poverty reduction. In addition, SMEs are important in terms of innovation, as they tend to be more innovative and flexible than larger enterprises. They often serve as suppliers or subcontractors to larger companies, by providing specialized parts or services that are necessary for larger companies to produce their own products. However, even though they can rapidly adapt to consumer needs, adaptation in terms of production, modernization and automation still requires substantial financial and knowledge capacity. This proves to be a challenge when transitioning into I4.0 not only in the face of global markets, but also in competition with large manufacturers or China. However, there is a common factor behind the success of SMEs in Europe – which is their ability to produce in a versatile manner, maintain close customer relationships, and quickly respond to the changing demands of the market as well as individual customer requests [6]. SMEs in the field of mechanical engineering play a crucial role in job creation, innovation, and supply chain dynamics, but their successful transition into I4.0 and competitiveness requires adaptation, modernization, and the ability to respond to the changing market demands.

1.1.2. SME issues in Industry 4.0

For the past two decades researchers and state institutions in Europe and across the world have been analyzing the potency and progress of the progress of manufacturing companies towards I4.0. This transition is perceived as a transition point from the current state of manufacturing and service industry into the new age. "Industry 4.0 will allow to exploit pillars such as the IoT, Big Data and data analytics, augmented reality (a virtual representation of the real world), cybersecurity, collaborative robots, AM, cloud computing, AI, and finally, 5G networks" [7]. Digitization and automation both prove to be a challenge to the human factor in manufacturing and to SME production lines that are slow and/or incapable of making a technological transition. "SMEs from less developed economies are more likely to struggle with Industry 4.0 transition, mainly due to the limited access to necessary regional ICT infrastructure or skilled labor" [8]. Here, such issues as time management and planning become crucial in order to not only adapt the automation, but also to create a smooth manufacturing process for SMEs.

Researchers [9] agree that even though SMEs make up the majority of the market, they face various challenges with regard to competition with the larger players in their respective industries. However, considering the topic of this thesis, it will be focused on the difficulties related to manufacturing companies. These companies are mostly struggling with finding qualified employees, as well as lack of understanding of the potential benefits of modernization [10], high costs, lack of technical expertise, concerns about data security [11], and some other issues. However, one of the key differences between SMEs and large companies in the manufacturing business is how efficiently they can incorporate automation into their production lines. This is where the ability to fund and control these large operations comes into play.

The adoption of AI in SMEs poses risks and fears that require attention. Compliance with regulations regarding discrimination, privacy, and data protection is crucial to avoid legal and ethical violations. Monitoring and oversight are necessary to address the potential biases and privacy breaches. Concerns exist regarding the loss of control over decision-making and functional capabilities. Job redundancy may arise as AI automates tasks, particularly in contact centers and financial services. Further research is needed to understand the implications of AI risks and misuse in SMEs [11]. The adoption of AI in SMEs necessitates careful attention so that to mitigate risks and address concerns related to legal and ethical compliance, privacy protection, biases, job redundancy, loss of control, and the need for ongoing research to understand the implications of AI misuse in SMEs.

The main problems with automation in SMEs include lack of knowledge and expertise, high investment costs, difficulty in integrating automation with the already existing systems, as well as uncertainty if there a return on investment can be expected [12]; also, one of the key issues, as identified by Salo *et al.*, is the lack of a clear automation strategy and struggle with identifying suitable automation solutions for their specific needs. This is also supported by Yu and Schweisfurth who suggested that knowledge about technology and its expected benefits were significant factors associated with the implementation of I 4.0 technologies, while the cost of technology by itself was not significant. They went even further to argue that the company size is not always significantly related to the ability and willingness to automate [13]. So, in terms of the ability and motivation to adapt I4.0 technology, such as automation or robotization in SMEs, is supposedly bound by uncertainty and lack of knowledge.

Mittal *et al*. agrees that stepping into I4.0 for SMEs is difficult not only due to lack of funding, but also due to lack of expert knowledge. He claims that the number of variables in manufacturing SMEs makes the process even more difficult, and success might be unobtainable without external expertise or adaptation of maturity models and self-assessment. But, even then, adaptation models vary, and there is no general outlook to adapting I4.0 technology which would work for every manufacturing SME [14]. However, here companies are required to have an in-depth awareness of their needs, and competencies, understand the benefits, and their ability to adapt I4.0 technology in their production systems (Fig. 2). For instance, a study by Masood and Sonntag investigated how SMEs in the UK perceive the benefit to difficulty ratio in adopting I4.0 technology in their manufacturing environments [15].

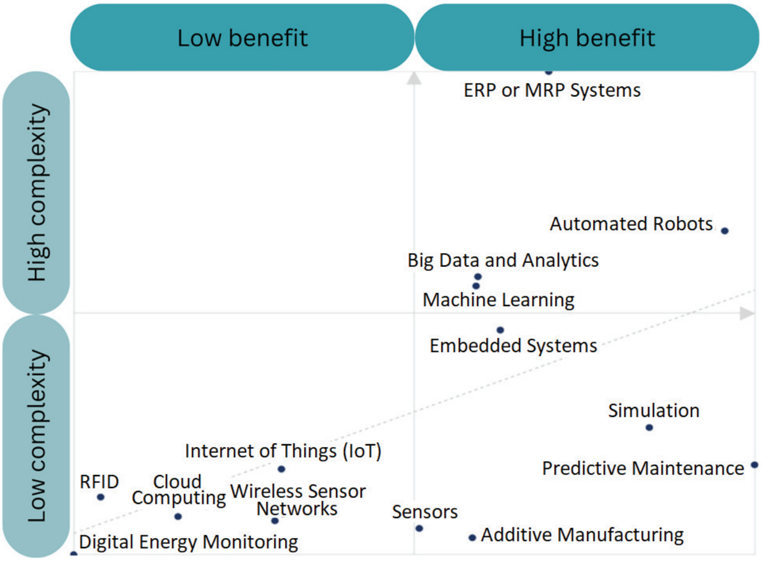


Fig. 2. Average Ratings for Technology Benefits and Challenges (adapted from [15])

Adaptation of I4.0 technology starts with self-assessment and the understanding of the manufacturing process within a given production line. Different companies have different starting conditions which lead to the development of variable strategies for every specific company. It is not a simple manner of 'automation for the sake of automation', but rather for creating seamless and self-sufficient production lines that are flexible and in coherence with the human factor.

1.2. Most Common Engineering Solutions in SMEs

Even though, as previously discussed, there are various barriers involving the transference of manufacturing SMEs to I4.0, there are undoubtedly various benefits to doing so. Both academia and business agree that in order to be more competitive with large enterprises or outsourcing companies, this shift is bound to happen. This section discusses the most common technology approaches that SMEs are adopting or should adopt in the future.

1.2.1. Internet of Things

IoT is pervasive across technology-oriented sectors, driven by the global expansion of internet networks, providing abundant access to smart devices, from homes to industries. It is recognized as a network of intelligent devices, virtually interconnected, aiming to enable collaborative, decentralized execution of tasks among various 'smart' devices, resulting in quicker task completion, simplified monitoring, maintenance, and automation [16, 17].

IoT enables the development of a network of industrial devices comprising sensors, robots, and actuators connected to communication technologies, enabling quick data monitoring, analysis, and manipulation. This facilitates the key features of I4.0, including horizontal and vertical integration and end-to-end engineering. IoT combined with I4.0 offers benefits, such as IT-OT convergence, reduced operations, better asset performance, cost minimization, and faster decision-making (Pivoto *et al*., 2021). The integration of various advanced technologies, including CPS, the Internet of Services (IoS), and others, with IoT enables the creation of personalized products (Manavalan & Jayakrishna, 2019). IoT technology always works with a wide range of technology, acting as a mediator between, for instance, smart sensors, robots, and humans.

In the industrial context, intelligent components – like RFID tags, sensors, and actuators – are integrated into equipment, driving industrial transformation by enabling machine-to-machine communication and automation [18]. This technology, known as the *Factory of Things* (FoT) or Industrial IoT for manufacturing, extends IoT principles to enhance production systems, while optimizing efficiency, reducing time to market, and increasing flexibility on the shop floor, in line with the I4.0 and Smart Manufacturing concepts [19].

According to Eurostat, "in 2021, just over a quarter (26%) of small enterprises used IoT, while large enterprises used it almost twice as much (48%). In medium-sized enterprises, nearly 2 out of 5 (37%) used IoT [...] lowest rates of IoT use were in [...] scientific and technical activities (25%)" [20]. Even though manufacturing SMEs are struggling to implement I4.0 technology into their production lines, IoT/FoT is probably one of the most accessible tools to SMEs due to the quite satisfactory return on investment [21, 22]. Also the technology is much more available and easier to implement into the already existing systems due to it being more plug-and-play than other I4.0 solutions, such as robotization or big data.

1.2.2. Cyber-physical production systems

CPSs utilize networks, such as IoT and cloud-based systems, to interact with and manage physical systems, such as machines, robots, and wireless sensors. By creating a digital representation of the production world through a smart network, CPSs can collect and manage data to make informed decisions on the physical world [23]. This digital representation is known as DT, which enables CPSs to model, simulate, and analyze real-world processes and predict outcomes. This results in an improved efficiency, safety, and productivity [24]. CPS is regarded as one of the key technologies to strive towards a true I4.0 factory, and thus it is deemed essential in the pursuit of the 'real' I4.0 implementation.

CPS enables the integration of various types of equipment, such as sensors, actuators, devices, machines, and robots, to form a smart community capable of gathering data and executing physical actions. This potential is achieved through multiple production levels, starting from sensors and progressing to machines/robots, and ultimately culminating in an entire factory [25]. CPS or CPPS possess self-capabilities, including self-adaptivity, self-organization, and self-learning, which enable autonomy. They work independently and make decisions autonomously, while remaining aligned with the organization's ultimate goal [25]. However, as discussed by Graessler [26] and Fantini [27], even though CPPS plays a crucial role in the automation of the manufacturing process, the human factor remains relevant in decision-making and creativity.

Even though CPPS is one of the key drivers in the full automation of any I4.0 enterprise, the implementation of such systems in SMEs is not a simple task. Researchers have identified an array of issues that SMEs are facing – and their range extends from costs, expertise, and lack of technical/IT personnel and ROI [28, 29] to the difficulty of the process of connectivity and integration into the already existing software/hardware systems [30]. Even though we see test frameworks and experiments from academics, a CPS system requires significant funding and expertise.

1.2.3. Big data analytics and artificial intelligence

BDA constitutes a fundamental pillar of I4.0 [31]. BDA and AI are revolutionizing the way manufacturing SMEs operate. By collecting and analyzing data from various sources, including sensors and supply chain partners, BDA enables SMEs to identify patterns and trends in their operations, optimize their processes, and reduce waste. The decrease in memory costs along with the increase in transfer speeds have made it feasible to gather substantial amounts of data from quantitative sensor systems [32]. BDA is a crucial component of I4.0, and it enables manufacturing SMEs to leverage data from diverse sources.

In their 2021 study, Bag *et al*. discuss that the adoption of BDA powered by AI had a beneficial impact on the sustainable manufacturing and circular economy capabilities of SMEs [33]. Overall, BDA and AI enable manufacturing SMEs to remain competitive in today's data-driven economy. In order to compete in the global market, manufacturing industries must consider factory digitization as a potential solution, which can be achieved through the use of BDA.

Both BDA and DT technologies present the contemporary industrial sector with fascinating opportunities to bring the manufacturing efficiency and green economy to new levels. According to the President of the European Commission, Ursula von der Leyen, there is an abundance of industrial data, of which 80% is currently being collected but left unused [34]. Moreover, according to *Digital Europe*, in order to achieve the *Digital Compass* target of 75% of EU companies using cloud/AI/big data by 2030, Member States and the European Commission need to act fast and establish a Multi-Country-Project edge/cloud initiative [35]. However, the main obstacles in SMEs to adapt the BDAAI technology are the absence of the IT infrastructure, inadequate data storage facilities, the absence of organizational strategy, and uncertainty regarding the benefits and long-term application [36]. The underutilization of industrial data, coupled with challenges, such as limited IT infrastructure, insufficient data storage, organizational strategy gaps, and uncertainty regarding long-term benefits, pose obstacles to the widespread adoption of BDAAI technology in SMEs.

1.3. Digital Twin for the Whole Process

In this section, we shall discuss DT technology on the manufacturing industry and explore the benefits it is offering. The DT technology has ushered in a new era in industrial IoT, by presenting not only significant research challenges, but also boundless opportunities. It is pivotal to address these challenges to fully unlock the potential of the DT technology in industrial IoT applications. The modeling approach we are proposing emphasizes the development of cost-effective DT-based services, by considering both human and technical factors in the ecosystem to create targeted DT models which would add value to business decisions while reducing complexity and costs. While SMEs often face significant challenges when adopting DT technologies, including the assurance of accuracy, standardizing data, integrating conventional machines, and addressing the slow standardization of data acquisition, cloud-based services and pre-designed software applications offer potential benefits to SMEs by integrating employees into computational decision-making processes, enhancing efficiency and effectiveness. The integration of AI, ML, physics-based models, and data-driven approaches will further enhance the capabilities of DT technology and drive the future of manufacturing.

1.3.1. Digital Twin enabling approaches

Overall, achieving comprehensive monitoring in industrial IoT through the DT technology poses significant research challenges and opportunities. The development of innovative sensing methods, efficient data processing and analysis algorithms, secure communication and networking protocols, and robust data fusion techniques will be crucial for realizing the full potential of DT technology in industrial IoT applications.

The proposed modeling approach facilitates the development of cost-effective DT-based services for businesses, while considering both human and technical factors in their ecosystem [37]. It focuses on creating targeted DT models that add value to business decisions by omitting unnecessary elements so that to reduce complexity and costs. Standardizing data, integrating unstructured data, smoothening the integration of I4.0 and DT components, and advancing analytics and ML algorithms are essential for furthering digital transformation and realizing the full potential of I4.0 [38]. While the presented DT model and communication framework effectively connect physical and digital assets and databases, there still remain certain areas for future research and improvement.

Researchers [38] propose a guideline for SMEs to adopt I4.0 technologies into their existing models by addressing key questions regarding "database management, data analytics, flow of data through sensors and networking, digitization, and systems integration." The authors recommend using OPC UA as the communication protocol, a structured *MySQL* database for data storage, and *Node-Red* software to wire together the various components. They also highlight the need for SMEs to consider such factors as costs, in-house expertise, and cybersecurity when implementing I4.0 technologies.

A study by Minos-Stensrud *et al*. [39] used real-time data from two Universal Robots UR3-robots obtained via the RTDE-interface, and the OptiTrack software provided Unity integration for tracking. This data was used to create a simplified DT which visually resembled the real UR3-robots. SMEs can now take advantage of the potential benefits offered by cloud-based services that allow them to adopt DT frameworks with the availability of pay-as-you-go options for most DTe solutions.

According to [38], multinational corporations offering pre-designed software applications and Product Lifecycle Management (PLM) solution fits with enabling DTe technologies for engineers are:

- *Predix* (General Electric Company, Boston, MA, USA);
- *Thingworx* (PTC Inc., Boston, MA, USA);
- *Mindsphere* (Siemens, Munich, Germany);
- *ANSYS* (ANSYS Inc., Canonsburg, PA, USA);
- *3DExperience* (Dassault Systèmes®, Vélizy-Villacoublay, France);
- *Altair* (Altair Engineering, Inc., Troy, MI, USA);
- *Oracle* (©ORACLE, Austin, TX, USA);
- *HEXAGON* (MSC Software, Newport Beach, CA, USA);
- *SAP* (Weinheim, Germany).

SMEs often face challenges in adopting DT technologies for their manufacturing needs. One major obstacle is ensuring the accuracy of DT in representing the physical system it is intended to model, which requires the collection, processing, and analysis of large amounts of data. Another challenge is the absence of a universally standardized format for data exchange. A continuous and reliable flow of verified and validated data between the physical and digital counterparts is also necessary. Integration with the conventional machines in manufacturing systems can limit the capabilities of DT services. Other difficulties include the slow standardization of data acquisition in production systems, high costs for new IT-environments, and the need to develop new skills and shift the roles of humans. However, the adoption of cloud-based services and pre-designed software applications can offer potential benefits to SMEs. DT can also integrate employees into computational decision-making processes, by providing immediate local information about the employee's current preferences, schedule, knowledge, and experience, and generating user feedback for computational decisions.

1.3.2. Physics-based modelling

Physics-based models are formulated through the application of fundamental principles, providing explicit physical meanings for each parameter and, consequently, ensuring a high level of interpretability [40]. The physics-based model provides interpretability and allows the exploration of various damage scenarios, while the ML classifier allows for fast evaluation of the physical twin in real-time [41, 42]. The use of a physics-based simulation model for predictive maintenance offers a number of advantages, including the ability to predict the condition and the status of the machine without stopping its operation, the continuous update of information at the component level, the ability to generate data for statistical analysis, and the ability to support the assignment of tasks to specific manufacturing resources [43]. To imbue the physical realism to DT, the governing equations derived through physical modelling must be solved. Over time, various discretization techniques have been developed, with some of the commonly used methods belonging to such categories as

FDM, FEM, FVM, and DEM [44]. Physics-based models in DT provide interpretability, real-time evaluation, and predictive maintenance advantages, while discretization techniques ensure physical realism.

The physics-based optimization approach can provide a more efficient and effective way to optimize the AM process parameters and part features. It can reduce the time and cost of the optimization process and increase confidence in the predicted properties of the parts. The DT approach can enable the development and use of such physics-based models in the AM process optimization [45]. The integration of physics-based optimization and the DT approach enhances efficiency, cost-effectiveness, and confidence in predicting the properties of the parts during the AM process.

1.3.3. Data-driven models

The advancement in data generation and storage, algorithms, and the changing needs of the manufacturing market have facilitated a shift in focus from the traditional simulation modelling to a more data-driven approach [2]. Physics-based models are commonly used; however, with the availability of abundant data in the DT context, data-driven modelling has gained popularity. This is facilitated by open-source libraries, such as *TensorFlow*, *Torch*, and *OpenAI*, and readily available high-quality training resources.

Resman presents a five-step approach to planning data-driven DT for discrete manufacturing systems, which encompasses system definition, process sequencing, specific data incorporation, DT creation with real-time feedback loops, and decision-support visualization [46].

In the DT context, AI and ML are making headway with the most commonly used supervised algorithms, such as Linear regression [47], Logistics regression [48], Supervised Support Vector Machine [49], and Artificial Neural Networks [50]. This is fueled by the emergence of new technologies regarding the generation and availability of data (i.e., sensors, open data, big data, AI, ML, etc.). The role of AI in data-driven DT is to dynamically update the DT using ML algorithms, such as long short-term memory (LSTM) neural networks. These algorithms can estimate the most up-to-date remaining useful life (RUL) of the physical asset by analyzing the data collected from various sensors deployed on the physical equipment [51]. DT relies on ML to analyze large amounts of data from various sources, such as sensors, social media, and satellite imagery, to identify patterns and make predictions about future events, and to optimize their performance by identifying areas for improvement and suggesting changes to the underlying models and algorithms. Overall, ML plays a critical role in enabling DT to become more accurate, efficient, and effective over time [52].

The development of advanced ML algorithms, such as deep neural networks and Gaussian processes, has contributed to the recent thrust in DT technology. These algorithms can be readily used to update the model and make future predictions. For example, some studies have used deep learning algorithms within the DT framework for prognosis and diagnosis of systems, while others have used Gaussian process regression for learning the evolution of the system parameters [53].

Liu presents a novel Refine-ACTDD algorithm, demonstrating its effectiveness in predicting the quality of die-casting and addressing challenges in detecting small defects within a large-scale dataset of aluminum alloy casting appearance defects (ALU-DEF). The integration of XGBoost and Refine-ACTDD for comprehensive quality prediction during and after the manufacturing process was thus achieved [54]. Wu proposes a dynamic data-driven DT approach for monitoring the remaining useful life of aircraft engines (RUL) by using sensors and simulation models. It employs an LSTM neural network to continuously update the DT with sensor measurements, providing real-time RUL estimates. The LSTM outperforms other RUL models in terms of accuracy. This framework holds promise for complex engineering products, and it could also be applied to the manufacturing equipment health management [51].

In recent years, there has been a notable shift toward data-driven models within the DT domain, driven by advancements in data technologies and the evolving manufacturing requirements. Traditional physics-based models are gradually giving way to data-driven approaches, facilitated by open-source libraries and readily available training resources. A structured framework for planning data-driven DT has been proposed, which is bound to aid in their implementation. These DTs increasingly rely on AI and ML techniques, such as linear regression, logistics regression, supervised support vector machines, and artificial neural networks, fueled by the proliferation of data sources, such as sensors and AI-generated data. Novel algorithms and integrations have also tackled complex challenges, exemplified by applications like aircraft engine remaining useful life monitoring. In essence, data-driven models, enriched by ML and AI, are reshaping DT across various sectors, by offering an enhanced accuracy, efficiency, and effectiveness.

1.3.4. Big data

Over the last few decades, the infrastructure for storing and processing large volumes of data has advanced significantly. There are now numerous platforms available to handle big data projects, including those for blending, integration, storage, centralized management, interactive analysis, visualization, accessibility, and security.

Both big data and DT are applied in various stages of the product lifecycle, from design to maintenance. However, there are barriers to the application of big data due to the security challenges in data sharing and the involvement of multiple parties [55]. In contrast, a DT can comprehensively process all data from design to retirement, thus making it more conducive to product development and maintenance. While big data focuses on data technologies, DT emphasizes cyber-physical integration. Their key technologies can be combined to enhance their application in the product lifecycle.

1.3.5. DT technology in SMEs

One of the main challenges in the development of a DT is to ensure that it accurately represents the physical system it is intended to model. Additional complexity necessitates the collection, processing, and analysis of more data, which makes projects too complex to be managed effectively. The second notable challenge faced by SMEs is the absence of a universally standardized format for data exchange. The third barrier pertains to the need for a continuous and reliable flow of verified and validated data between the physical and digital counterparts [56]. The accuracy of DT poses a significant challenge for SMEs, as they require collecting and analyzing large amounts of data, thereby making projects difficult to manage. It is necessary to address the challenges of creating a dependable DT in practice, particularly for manufacturing applications where strict demands for timeliness, accuracy, and reliability must be met [57]. To achieve a connected and autonomous manufacturing ecosystem, the challenges of creating a dependable DT in practice, which must meet the strict demands for timeliness, accuracy, and reliability, need to be addressed.

DT encounters numerous situations where conventional machines are used in manufacturing systems. This traditional approach restricts the capabilities of DT services unless there is a two-way connection to exchange information between the DT and its physical counterpart [58]. For effective information exchange between the DT and its physical counterpart, a two-way connection is essential, which the traditional approach of using conventional machines in manufacturing systems may limit.

The most notable difficulties include the manual acquisition of motion data, which conflicts with the requirement for real-time availability. Moreover, the manual acquisition of motion data snapshots limits the potential of simulation, and a central information system is required for decentralized data acquisition. The slow standardization of data acquisition in production systems hinders agile and adaptable system implementations. Additionally, the excessively high costs for new IT-environments can inhibit the application of vertical I4.0 [59].

To acquire production data in SMEs for DT, two main systems are commonly used due to the highly heterogeneous database and the insufficient quality of the data. These are sensor-based tracking and machine vision [59]. Inaccurate data resulting in erroneous decisions necessitates human intervention to recognize and correct errors, which requires new skills. Therefore, the integration of DT into production processes requires the development of new skills and a shift in the roles of humans. However, the concept of DT can also be extended to include the representation of humans in the virtual world. This requires information reflecting the human's role within the production system. The same objectives that apply to the technical DT, such as increasing the quality, avoiding errors, and reducing time to market, also apply to the human DT. The human DT should include information on the individual's specific tasks, abilities, and, potentially, information that can be used to customize assistance systems to improve job performance [60]. This approach can improve the overall performance and efficiency of the production system by better integrating humans into the DT-driven smart manufacturing environment. Zhang *et al*. (2023) suggest that examining workers' learning patterns and the DT model outcomes associated with them can facilitate their adaptation to changes in manufacturing and enable the development of new methods for transforming past experiences into accurate statements [61]. The DT model can enhance their ability to adapt to changes in manufacturing and improve the overall efficiency of the production system.

1.4. Real-Time Production Tracking and Planning (Lead Time Adjustment)

Real-time production tracking, powered by advanced technologies and data analytics, provides substantial benefits for SMEs by offering immediate and comprehensive insights into manufacturing processes. This enables real-time monitoring and control of the production stages, enhancement of operational efficiency, quality management, and resource optimization. SMEs can track KPIs in terms of, for instance, production output, cycle times, machine downtime, and inventory levels, thereby identifying bottlenecks, streamlining operations, and making data-driven decisions. With real-time visibility, SMEs can proactively address issues, reduce waste, boost productivity, enhance customer satisfaction, and gain a competitive edge. This monitoring empowers SMEs to optimize resources, cut costs, and adapt to market changes, thus fostering growth and sustainability in a dynamic business environment.

Manufacturing companies often face challenges when it comes to tracking end-to-end manufacturing due to the diverse range of machines used from different manufacturers. Maintaining a single system for tracking can be difficult, expensive, and challenging to maintain, especially when production lines are undergoing continuous optimization and redesign to improve their performance [62]. However, effective tracking of manufacturing parameters, such as the production count, runtime, and other KPIs, requires a high degree of tracking resolution. Inadequate tracking resolution can result in inaccurate and insufficient tracking reports that may hinder the optimization process. While many modern machines used in manufacturing plants come while being already equipped with operation tracking features, SMEs may still rely on older machines which, unfortunately, lack such features. End-to-end manufacturing tracking is challenging for companies due to diverse machine types, which therefore necessitate a cost-effective system with high resolution for accurate optimization reports, especially for SMEs with older machines lacking tracking features.

1.4.1. Data Acquisition Systems

Data acquisition is a crucial aspect of mechatronics as it enables the collection and analysis of data from physical systems by using sensors and dedicated hardware. The collected data can be processed and manipulated by using software which can be customized according to the type of data being collected. DAS has come a long way since its development by IBM in the 1960s, and now it is possible to measure and analyze almost any form of a physical system. With the advancement in technology, it is now possible to use a single PC, a tablet, or a smartphone to aggregate all the collected data, thus making it easy to analyze and manipulate the processes.

The fact that existing DAQifi devices run on their own power and can send the collected data over a Wi-Fi network makes them ideal for situations where having a dedicated PC workstation is simply impossible, such as in many industrial processes or situations where the system under study is inherently mobile [63].

Da Costa *et al*. (2023) notes that wireless communication technologies such as RFID, Bluetooth, and Wi-Fi are identified as critical for real-time data transmission and tracking of production. Cloud computing and BDA are also highlighted as essential tools for processing and analyzing the large amounts of data being generated [64].

Despite the benefits of data acquisition, processing and analyzing large amounts of data generated requires essential tools, such as cloud computing and BDA.

1.4.2. Sensors

The implementation of virtual manufacturing improvements in factories begins with observing production, recording lifecycle data, and utilizing sensors to collect real-time information for connecting manufacturing processes with virtual simulations and software systems. Sensors, including temperature, proximity, accelerometer, infrared, pressure, light, and ultrasonic types, are crucial for data collection and real-time monitoring of machinery and production [65].

Real-time production tracking can be enhanced with the use of IoT tracking. IoT-enabled devices and sensors can be placed throughout the manufacturing process to track various parameters, such as the production count, runtime, temperature, humidity, and more. Overall, the approach taken by SMEs for real-time production tracking will depend on such factors as the size of the operation, the available resources, and the complexity of the production process. Real-time production tracking in manufacturing SMEs can be carried out through a variety of methods.

IoT devices are used for collecting real-time data from the production process. These devices include RFID sensors, temperature sensors, and humidity sensors, which are attached to the products or the production environment to collect the relevant data [66]. Zhang *et al*. note that this approach not only improved efficiency and reduced costs, but also contributed to environmental sustainability by extending the life cycle of products through remanufacturing [67]. Da Costa *et al*. (2023) claim that the use of IoT devices can provide better visibility and transparency in the supply chain, thereby allowing for more informed decision-making. Authors suggest that data analytics can be used to identify hotspots for enabling targeted interventions to reduce waste [64].

Elías *et al*. (2020) describe the MD and Machine Learning Platform (MDML), which enables real-time monitoring and control. The MDML platform employs a combination of edge computing and cloud-based processing to enable real-time analytics and decision-making [68]. The platform utilizes various IoT communication protocols, including MQTT and CoAP, to ensure efficient and reliable data transmission between the edge devices and the cloud platform. Hamilton proposes a framework which integrates "real-time big data analytics, sustainable wireless networks, and IoT-based" DSS for enhanced manufacturing performance [69].

Real-time production tracking in manufacturing SMEs can be carried out through various methods, such as the use of IoT-enabled devices and sensors. The use of IoT devices provides better visibility and transparency in the supply chain, enabling informed decision-making. The integration of real-time BDA, sustainable wireless networks, and IoT-based DSS can facilitate real-time analysis and decision-making, which ultimately leads to an improved manufacturing performance within SMEs.

1.4.3. Communication and means of production tracking

Effective communication technologies are critical for real-time production tracking in the age of IoT. With the increasing complexity of modern manufacturing processes, it is essential to collect and analyze large amounts of data in real-time to optimize efficiency, reduce downtime, and improve the product quality. This requires reliable and robust communication between various IoT devices and sensors to facilitate seamless data collection and analysis. Jedermann *et al*. discuss the challenges and opportunities in remote monitoring of perishable products by using IoT [70]. The authors also emphasize the need for energy-efficient communication protocols and low-power sensors (RFID, wireless sensors, GPRS, 3G, and 4G technologies). Tsang *et al*. suggest an approach regarding the employment of IoT technology (GPS, and cloud computing technologies) to monitor temperature and humidity in real-time and analyze the data by using a fuzzy expert system [71]. The system alerts the users when the temperature or humidity exceeds the predefined threshold levels, thus allowing the users to take corrective actions immediately. Hodara and Skaljo discuss the evolution of wireless communication technologies from 1G to 5G and their potential applications in IoT [72]. They highlight the key features of 5G, including ultra-low latency, high reliability, and massive connectivity, which are critical for real-time data communication in industrial applications. The authors also discuss the challenges in deploying 5G networks in industrial settings, such as interference and compatibility issues with legacy communication systems. Torres-Sánchez *et al*. use the Zigbee wireless communication protocol (Wireless sensor networks and LoRaWAN technology) to establish a reliable and low-power communication link between the sensors and the gateway [73]. The gateway then transmits the collected data to a cloud server for storage and analysis. Ramírez-Faz et al. suggest using Arduino-based temperature sensors and Raspberry Pi-based DAQs [74].

One common approach is the use of the barcode or RFID scanning technology to track materials, work-in-progress, and finished goods as they move through the production process. The three main components of an RFID system are RFID tags, readers, and the middleware software. The RFID tag has an integrated circuit chip and an internal antenna, and the reader communicates with the tag to exchange information [66, 75]. The RFID technology has become increasingly popular in various industrial applications due to its unique features and superior capabilities compared to other identification technologies. In particular, RFID can significantly enhance real-time visibility within the production environment [76]. However, there is a need to evaluate the effectiveness and feasibility of the RFID technology in different manufacturing scenarios in a fair and objective manner to ensure that the anticipated goals are achieved, especially considering how I4.0 is moving towards smarter, sensor-based solutions.

SMEs usually track production through a combination of manual record keeping and basic electronic data recording, such as using spreadsheets or standalone software applications. They may also use basic barcode or RFID technologies for material handling and inventory management [77]. Lack of automation and data integration in SMEs makes it difficult to monitor and analyze production processes in real-time [78]. The development of a production tracking system requires a significant amount and volume of resources, such as sensors, data storage, and computational power, to which SMEs may have no access due to their relatively limited financial and technological resources [79].

Real-time production tracking in manufacturing SMEs can be carried out through a variety of methods, including IoT devices, which can collect real-time data from the production process. SMEs usually track production through a combination of manual record keeping and basic electronic data recording, such as the use of spreadsheets or standalone software applications, which limits their ability to monitor and analyze production processes in real-time. Therefore, there is a need for SMEs to invest in advanced technology, such as DT and IoT devices, to improve their manufacturing processes and stay competitive in the market.

1.5. Enterprise Resource Planning and other Systems

Manufacturing is a complex process which requires the coordination of various activities, from planning and design to production and quality control. In recent years, several systems have been developed to improve the efficiency and quality of manufacturing processes.

An ERP system is an enterprise-wide information system which integrates and controls all the business processes in the entire organization to enhance efficiency and maintain a competitive position [80]. The implementation of an ERP system is important for SMEs to follow the best practices of the industry and adapt to the changing environment. However, the implementation process of an ERP system is complex and difficult, and the success percentage is relatively low. Therefore, a systematic and easily understood framework is required to aid SMEs in implementing ERP systems successfully [81]. It is also suggested that SMEs can benefit from SaaS ERP systems in terms of real-time data, visibility, and standardized processes and information, as well as improved collaboration and performance [82]. The substantial uptake of ERP systems among SMEs has played a significant role in generating value for these firms. It has empowered them to design products and services that provide exceptional customer value, consequently setting them apart from their competitors. Building a physical IT infrastructure along with information systems is also necessary to support open innovation. While case studies can provide valuable insights, quantitative studies are needed for generalization [83]. The four main criteria identified as having a strong positive correlation with ERP implementation in SMEs are the product, the people, the project, and the business process. It is important to note that if one of these variables is missed, there may be a significant impact on ERP implementation in the organization. The study also concluded that low-ranking ERP systems are more manageable by SMEs than high-ranking ERP systems [84]. ERP systems are vital for SMEs to enhance efficiency and competitiveness, but successful implementation requires a systematic framework and consideration of the key criteria for success.

ERP systems are comprehensive business management software integrating all aspects of a company's operations, from finance and accounting to inventory management and customer service. ERP systems can automate and streamline business processes, thus allowing companies to optimize their operations and reduce costs. In manufacturing, ERP systems can provide real-time visibility into inventory levels, production schedules, and quality control. Adoption of ERP systems has become increasingly prevalent, as a means of enhancing the overall productivity and efficiency.

ERP systems, which "integrated business processes such as manufacturing, project management, financial, distribution, inventor management, human resource, maintenance and service, accounting and transportation," eventually came to surface in the late 1980s and early 1990s [85]. ERP systems have yielded substantial advantages for organizations, including heightened productivity, an improved access to precise and timely information, enhanced workflow, diminished paper dependence, facilitated knowledge sharing, stringent control, and streamlined business processes through the coordination and integration of information across various departments [85].

These trends are shaping the future of ERP technology by making it more accessible, flexible, and intelligent. For example, data cloud acceleration is a game-changing trend which allows users to access ERP software from anywhere with an internet connection, while AI and ML can help organizations automate routine tasks and make better decisions based on data insights. Mobile ERP enables users to access critical information on-the-go, while hybrid ERP combines on-premises and cloud-based solutions for greater flexibility [86]. SMEs have increasingly adopted a modular approach to ERP implementation, which allows them to implement specific modules of the system as needed, rather than implementing the entire system at once. This approach can help SMEs manage costs and minimize disruption to their operations.

An increasing use of cloud-based ERP systems can help SMEs manage costs and minimize the need for IT infrastructure. The adoption of modular ERP systems allows SMEs to implement specific modules of the system as needed, rather than implementing the entire system at once. This approach can help SMEs manage costs and minimize disruption to their operations [87]. However, barriers to adoption, such as the lack of expertise, resistance to change, and concerns over data security, need to be addressed to ensure successful implementation and integration of these systems into SMEs' operations.

The reference architecture model of ERP systems helps in addressing the problems faced by businesses during the ERP life cycle by systematically grouping the identified issues according to the different levels of systems architecture. This approach allows for related challenges to be attributed to the respective research domains and develop the solutions accordingly. The user interface of ERP systems lags behind other system categories concerning the adaptability to the requirements of individual users Future developments may focus on the needs for special user groups, such as young and old users, or beginners and advanced users [88]. On the other hand, research recommends that ERP system designers should "prioritize productivity and simplify user jobs when improving and designing new ERP systems" so that to increase employee satisfaction and improve the actual benefits derived from the ERP system [87]. Moreover, systems like SAPERP are designed to help organizations streamline their operations, improve efficiency, and reduce costs [87]. The purpose of including human resources in an ERP system is to manage employee data, such as payroll, benefits, performance evaluations, and training. By integrating human resources into an ERP system, organizations can streamline their HR processes, reduce errors, and improve data accuracy.

Doyle and Cosgrove (2019) in their experiment reported using MTConnect, IoT devices, and open-source software from the BEinCPPS architecture. The incorporation with the facility's ERP system led to a reduction in production management responsibilities, enhanced resource management, and simplified operator reporting. The identified areas of improvement encompassed Part Program Version Control, Job Scheduling, and Local/Remote Visualization of machine and Work Order Status. These areas were targeted for digitization to facilitate improved Production Scheduling and OEE due to up-to-date knowledge of the machine and production status [89]. The most commonly used programming language for ERPs is Java. PHP and Python are the next most commonly used languages. Other common tools, such as Point of Sale, eCommerce module, Website Management Tool, Subscriptions Management Tool, and Help Desk, are also common [90]. Integration of MTConnect, IoT devices, and open-source software with an ERP system enabled improved production scheduling, resource management, and OEE by digitizing key areas and providing real-time machine and production status information.

1.5.1. Enterprise Resource Planning systems in SME settings

ERP systems can have a positive impact on the integration of the supply chain with suppliers, customers, and processes [91]. ERP systems have been found to be beneficial for businesses of all sizes, including SMEs. However, as with any I4.0 technology, there are barriers that SMEs may face when implementing ERP systems. These barriers include limited financial resources, limited IT expertise and resources, resistance to change, dependence on external consultants, limited project management experience, informal communication channels, flexible organizational structure, centralized decision-making, and the ownership type [92]. "Top management support significantly and positively correlates with the intention to adopt cloud-based ERP system in manufacturing SMEs" [93]. Elements like the security of cloud systems and data privacy, cost-efficiency, reliability of Internet connectivity, support from top management, and competitive pressures can influence the inclination of SMEs towards adopting cloud-based ERP systems. While cloud-based ERP systems offer a cost-effective solution for SMEs, there are still challenges to their adoption, such as aligning the software with business processes and providing customized governance and training [94]. Thus, SMEs face various barriers when implementing ERP systems such as limited financial and IT resources, resistance to change, and dependence on external consultants. This suggests that one potential barrier for SMEs in ERP implementation could be a lack of control over the system due to the inherent reliance on external providers. However, the importance of management factors remains, which could include human factors, such as leadership, communication, and employee training [95]. Implementation of ERP systems can positively impact the supply chain integration, but SMEs may face barriers, such as limited resources, resistance to change, and dependence on external consultants, while cloud-based ERP systems offer benefits but require considerations, such as data privacy and alignment of the software with business processes.

SMEs should have the necessary data and information management practices in place to ensure that the ERP system can be effectively integrated into their existing business processes. Critical failure factors include poor data quality and management, inadequate training and support, resistance to change, lack of effective communication and collaboration, incompatibility with the already existing IT infrastructure, and insufficient resource allocation [96]. However the benefits of cloud ERP systems, such as an increased reliability, lower costs of ownership, and quick deployment, can be particularly advantageous for SMEs with limited resources. This factor refers to the skills, knowledge, and attitudes of employees towards the adoption of cloud ERP systems. The authors suggest that employee training and involvement in the adoption process can help overcome resistance to change and increase the likelihood of successful adoption [97]. Without these prerequisites, the implementation of ERP solutions may not be successful. Generally, best practices may include conducting a thorough analysis of the organization's business processes and requirements, ensuring compatibility with the existing IT infrastructure, developing a comprehensive implementation plan, providing adequate training and support to end-users, and regularly monitoring and evaluating the ERP system's performance.

1.5.2. Manufacturing Execution Systems

MES systems are used to monitor and control production processes on the factory floor. These systems utilize sensors and other data collection methods to track the status of machines, materials, and personnel. MES systems provide real-time data on production activities, thus allowing for continuous monitoring and optimization of manufacturing processes. MES systems are critical for achieving the desired level of efficiency in the manufacturing process.

MES enhances performance, quality, and agility in globalized manufacturing [98]. The new generation of MES aims to offer real-time insights, serve as a manufacturing cockpit, and support I4.0 technologies, particularly in the context of smart factories. MES bridges the information gap between business and shop-floor layers, thus facilitating automation, and aligning with reference architectures like SIMA [99].

The design of generic MES systems (Fig. 3) identifies six key components of MES systems: equipment management, production process management, quality management, order management, production scheduling management, and resource management [100].

Mogensen (2019) used a wireless MES solution "at the Smart Production Lab facilities at Aalborg University, allowing the removal of Ethernet cables between modules in a production line setup, and thus enabling a faster re-configuration of the production facilities." The measurement results revealed that all the studied solutions had "one-way latencies significantly below the 2 s survival time set by the MES" [101].

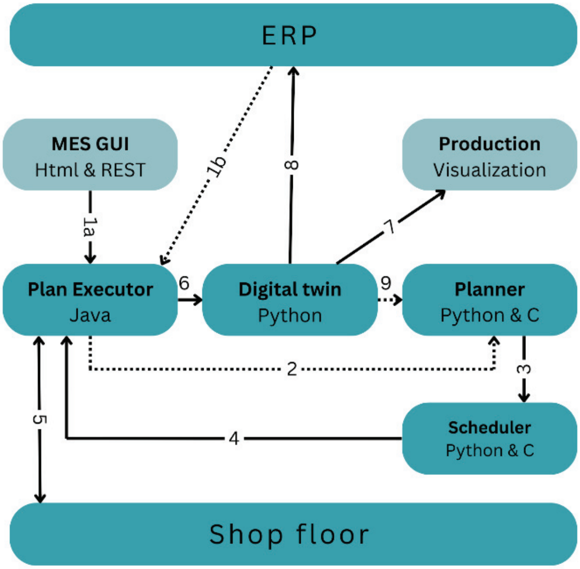


Fig. 3. Proposed architecture of the new generation of MES (adapted from [100])

The possibilities of MES, ERP and other I4.0 applications are limitless. For instance, Barni suggests that data could be captured from ERP and MES systems and used in conjunction with ML/AI to interact with the agent-based modeling approach which is the core of DT [102].

This would offer further understanding of the potential outcomes and assist the firm in making informed investment decisions regarding new machinery, recruitment or training of personnel, and bidding on new customer projects.

1.5.3. Computer-Aided Process Planning systems

CAPP systems are computer-based systems which automate the creation of manufacturing process plans and work instructions. CAPP systems use computer-aided design (CAD) models to generate detailed process plans, including the tools, materials, and operations required to produce a given product. By automating this process, CAPP systems can reduce the time and cost required to create manufacturing plans and ensure that plans are consistent and accurate. CAPP systems can play an essential role in the reduction of the product development cycle, and the optimization of the production process.

Efficient CAPP can determine crucial factors, such as cost, competitiveness, production planning, and efficiency. However, automating CAPP has been challenging due to its multidisciplinary nature. CAPP requires accurate analysis of inputs, such as feature technology, dimensions, materials, and process capabilities, to generate process planning. The final output includes process selection, sequence of operation, cutting tools, cutting conditions, jigs and fixtures selection, tool path identification, and cost and time estimation [103]. Dynamic CAPP is used for flexible process planning to cope with product variety. Potential energy-saving strategies can be developed by using advanced CAPP systems during product design and process planning. This involves connecting CAPP systems using web systems to share data and increase sophistication, applying fuzzy logic and optimization methods, developing green manufacturing systems, and utilizing virtual manufacturing systems to analyze and modify the process of part production [104]. Automating CAPP is challenging due to its multidisciplinary nature, but it is crucial for a number of factors including cost, competitiveness, and production planning. Dynamic CAPP enables flexibility and energy-saving strategies, while advancements in connectivity, fuzzy logic, and virtual manufacturing enhance its capabilities.

Basinger *et al*. demonstrate time reductions and capabilities of a patient-specific bone plate planning system compared to manual methods [105]. Chen and Sun propose hybrid-two-stage optimization algorithms to assess i-CAPP readiness for I4.0, tested with a five-axis CNC tapping machine [106]. Yunitarini and Widiaswanti introduce an integrated CAPP and bill of a material system to enhance competitiveness and responsiveness in manufacturing [107]. Rojek employs neural networks for machine and tool selection in process operations, thereby aiding process engineers [108]. Susac *et al*. propose an AVAL method-based algorithm for product launching sequence in CAPP [109]. Andriani *et al*. find CAPP more effective in terms of time, cost, accuracy, and conformity with tangible results compared to the conventional methods [110]. Trstenjak *et al*. stress the importance of educating workers about I4.0 and CAPP concepts to plan digitization strategies, while highlighting differences between SMEs and larger companies in digital adoption [111].

In conclusion, CAPP systems offer unique features and benefits for manufacturing organizations, including improved process management, reduced processing time, enhanced competitiveness, and increased accuracy.

1.5.4. Decision support methods in manufacturing

DSMs in manufacturing encompass a diverse array of techniques and tools designed to aid decision-makers in making well-informed and effective choices pertaining to various aspects of production, resource allocation, process optimization, and the overall performance enhancement. These methods leverage data, models, and algorithms to furnish valuable insights and recommendations which facilitate informed decision-making. Within the manufacturing context, several common DSMs are utilized, including data analytics, simulation, optimization algorithms, DTr and ML, expert systems, sensitivity analysis, MCDA, real-time monitoring and control, and business intelligence (BI) dashboards.

Lack of DSS studies tailored for SMEs has been observed. SMEs face unique challenges in developing and implementing sustainable DSS. To overcome resistance to sustainable development, case studies demonstrating the benefits of sustainable manufacturing in all LC phases for SMEs are recommended [112]. However, DSS is adopted in a variety of sectors, such as healthcare settings, including hospitals, clinics, and primary care practices, and can be tailored to specific patient populations or clinical specialties [113]. DSS are commonly used in several areas of human resource management (HRM), such as HR planning, talent management, recruitment, and performance management [113].

Edge computing is an integral component of the broader IoT system aimed at resolving latency issues and overcoming barriers associated with the conventional cloud architecture. It facilitates on-site data processing, by enabling continuous monitoring, analysis, and connectivity. By eliminating the necessity to access the cloud for time-sensitive insights and real-time decision-making, edge computing reduces the distance between the user and the server. The primary objective of edge computing is to swiftly provide data, while also ensuring that companies can define its advantages based on their specific use cases, objectives, and challenges they aim to address. In a production environment, IoT edge computing may be confined to a single building [114].

Analysis of the commonly used DM algorithms, such as ARS and AA, demonstrates their relevance and applicability in the context of intelligent manufacturing IoT. Furthermore, the research on DTr mining algorithms and the generation and pruning of DTs highlights their effectiveness in processing and extracting meaningful insights from vast datasets [115]. Sensitivity analysis serves as a technique to assess the impact of changes in variables and parameters on manufacturing outcomes. By identifying those critical factors which significantly influence production processes, decision-makers can focus on optimizing those aspects to improve the overall efficiency of their operation. In agricultural settings, different algorithms depending on their specific application(s) and task(s) are used. For example, the AgriSupport II system, CPLEX optimizer, serves as a decision-making tool, while other ADSSs may use different optimization or ML algorithms. APS tools use advanced algorithms and simulation techniques for global optimization, while taking into account all the constraints found at different layers of the chain. These techniques can evaluate several alternatives and choose the best option. For example, APS modules include demand planning, production planning, production scheduling, distribution planning, and transportation planning [116]. Allaoui suggests a platform called the *Collaboration Planning Tool* (CPT) which informs "the development of multi-party collaborative relationships across the entire network to improve the overall sustainability of delivered products." "CPT supports developing aided decision-making and planning applications, taking into account dimensions not typically covered by existing supply chain planning systems, like Advanced Planning Systems (APS)” [117].

A hybrid model combines DTr and artificial neural network models to efficiently provide decision support. A DSS is developed through the ML approach, and it achieves high prediction performance compared to data balancing techniques [118].

MCDA methods aid decision-makers in evaluating alternatives based on multiple criteria or objectives. The weighing of different factors enables decision-makers to make choices which align with the organization’s overarching goals and priorities.

The adoption of data-driven models and the integration of ML and AI technologies within the DT framework have ushered in a transformative era for industries, particularly in manufacturing and engineering. This evolution has been fueled by the confluence of increased data generation and storage capabilities, more advanced algorithms, and changing market dynamics. The notable transition from the traditional physics-based models to the data-driven approaches is evident, with open-source libraries and ample training resources providing essential support. However, a persistent challenge in this landscape has been the ‘lack of knowledge’ concerning real-time data analysis and decision-making. Fortunately, it is increasingly apparent that this hurdle can be effectively addressed through the implementation of DSSs within the DT ecosystem. These systems leverage the power of AI and ML to not only process vast volumes of data, but also to distill actionable insights, thereby offering a promising solution to bridge the knowledge gap.

1.6. Optimization Task Calculations in Production

Optimization task calculations involve determining the most efficient way to produce a desired product, considering various factors such as time, cost, quality, and resources. These calculations can be performed by using various optimization techniques, including mathematical modelling, simulation, and AI. Automation plays a significant role in optimizing production processes, as it involves the design and development of machinery, tools, and automation systems which help to streamline and automate various tasks involved in production. These systems are typically designed to reduce human error, improve efficiency, and increase productivity. Various methods are employed to perform optimization task calculations within the manufacturing sector, taking into account factors such as specific requirements, automation levels, organizational objectives, and preparedness.

Optimization tasks involve finding the most efficient and effective solutions to complex production challenges. Its aims include maximizing productivity, minimizing costs, and improving the overall performance. For SMEs, which often operate with limited resources and face fierce competition, optimization becomes a critical factor in achieving operational excellence and staying competitive in the market. By employing advanced mathematical models, algorithms, and computational techniques, optimization task calculations provide SMEs with valuable insights into their production processes, thus enabling them to make informed decisions regarding resource allocation, scheduling, inventory management, and capacity planning. Zhang proposes a method for scheduling production tasks in an intelligent way, while considering multiple constraints, such as the task priority, time limits, and urgent task insertion. The objective is to minimize the waiting time and the completion time by using the BAS algorithm to solve the problem [61]. Jin *et al*. provide an algorithm which reuses "past experiences of one task to generate a population pool for the next iteration of another task, enabling explicit genetic transfer between different tasks and accelerating the population convergence speed" [119]. Meanwhile, other authors analyze the task assignment problem in terms of three objectives: minimizing the total processing time, minimizing the makespan, and minimizing the maximum workload of all machines. Then, they develop a multi-objective genetic algorithm to solve the optimization problem [120]. The proposed model was tested in a case study, and the results showed that the genetic algorithm was able to find the optimal solutions for the task scheduling and management problem. The authors conclude that the use of genetic algorithms can lead to significant improvements in the efficiency and effectiveness of production processes [121]. This approach represents a departure from the traditional manual or rule-of-thumb methods, while introducing a novel and data-driven approach to production management. Through optimization task calculations, SMEs can identify bottlenecks, streamline workflows, reduce waste, and optimize their supply chain, which results in an increased efficiency, improved product quality, and enhanced customer satisfaction.

An approach developed by Liu *et al*., specifically, MTO-MCSCO, considers multi-functionality manufacturing tasks and uses a new pattern called *Multi-Composition for Each Task* to combine incompetent composite services into a whole to perform each of the multi-functionality manufacturing tasks collectively [122]. A TBBO algorithm can provide a more effective way to solve the multi-objective urgent task-aware CMSC problem, which can help manufacturing systems to optimize their service composition and improve their overall performance [37]. On the other hand, Li *et al*. present two multi-objective-meta-heuristic algorithms, namely, the *ACO-based multi-objective algorithm* (MACO) and the *NSGA-II-based multi-objective algorithm* (MGA), to solve the scheduling problem. The algorithms consider constraints, such as subtask dependency and service execution limitations [120]. New approaches and algorithms, such as MTO-MCSCO and TBBO, have been proposed to optimize the service composition and scheduling in manufacturing systems, thus ultimately enhancing the overall performance and efficiency.

Through a review of the currently existing research, it has been found that approaches considering both the technical data and the capabilities and performance of employees are uncommon. For instance, a smart production planning and control system described in [123] does not address the issue of the human workforce. Similarly, in Turker's work, a DSS for Dynamic Job-Shop Scheduling using real-time data with simulation only considers workstations and their operations, without even considering the employees who perform the tasks [124]. Additionally, a study on increased productivity of operators by Ito *et al*. does not address the issue how to select employees based on their specific capabilities for certain tasks, or how to handle situations when an employee is absent [125]. The abovementioned sources, even though they present complicated and multi-faceted algorithms and task calculation solutions, hardly ever attempt to incorporate the human factor into their work. Only a handful of studies have actually incorporated the human factor in compiling their working task allocation systems.

Zhang *et al*. performed research where the goal was to find the best way to assign tasks to human workers and robots so that to achieve a balance the between job cycle time and human fatigue. The paper proposes a task scheduling model which includes microbreaks within job cycles to prevent human fatigue accumulation [126]. Zhang *et al*. and Yao optimize this process, and the paper introduces a dynamic and multi-objective optimization model and algorithm that considers the collaborative benefits and risks of the co-operators. It focuses on optimizing the supply chain scheduling process by considering the collaborative benefits and risks of the co-operators. The algorithm can indirectly account for the human factor by considering the performance and satisfaction of the co-operators in the scheduling process [127]. These considerations can lead to improved performance, worker satisfaction, and the overall efficiency in manufacturing processes.

Babor *et al*. investigate a hybrid scheduling model and five multi-objective optimization algorithms to find the optimal schedules. While the makespan influenced production costs, minimizing oven idle time could result in energy conservation. Some solutions with the shortest makespan, however, exhibited higher oven idle times, implying potential energy wastage. Multi-objective algorithms provided solutions with reduced energy waste and better tradeoffs. NSGA-II outperformed other algorithms, and it was followed by SPEA2. GDE3 performed slightly better than OMOPSO and SMPSO [128]. The use of multi-objective optimization algorithms can help achieve optimal schedules which would minimize energy waste and production expenditure.

In a study presented by Rezig *et al*., it is indicated that a mathematical model was implemented and tested on a discrete event system within the laboratory setting at the University of Lorraine, Metz, France. While Petri net modeling is commonly used for flexible manufacturing systems, this article demonstrates that complex production issues can be effectively controlled by using mathematical modeling, thus obviating the need for more intricate tools, such as colored Petri nets. As a result, the mathematical model's output facilitated the implementation of a Petri net supervisor using STEP7 software [129]. This demonstrates the potential of mathematical modeling as a practical and efficient solution for managing production systems.

Moreover, the ongoing advancements in optimization algorithms and computational capabilities present SMEs with new opportunities to tackle increasingly complex production challenges, while also paving the way for continuous improvement and innovation within their operations. Thus, the significance and novelty of optimization task calculations in manufacturing SMEs lie in their ability to provide a systematic, analytical, and forward-looking approach to production management, which would lead to tangible benefits and long-term competitiveness.

In manufacturing, linear programming and nonlinear programming are pivotal optimization techniques. Linear programming is employed when production processes exhibit linear relationships between the involved variables, thus facilitating such tasks as resource allocation and production scheduling. On the other hand, nonlinear programming is vital for addressing more complex manufacturing scenarios characterized by nonlinear relationships between the variables, as seen in chemical processes or intricate production constraints. Nonlinear programming utilizes methods like gradient-based techniques and genetic algorithms to optimize nonlinear functions. The choice between linear and nonlinear alternatives depends on the nature and complexity of the manufacturing problem, thus enabling manufacturers to make data-driven decisions so that to enhance efficiency, reduce costs, and optimize their production processes.

In conclusion, optimization task calculations are crucial in production as they determine the most efficient ways to achieve the desired outcomes while considering factors like time, cost, quality, and resources. These calculations, employing techniques such as mathematical modeling and AI, enable SMEs to improve productivity, reduce costs, and enhance the overall performance. By integrating advanced algorithms and considering the human factor in task allocation, SMEs can streamline workflows, optimize the supply chain, and achieve long-term competitiveness. The ongoing advancements in optimization algorithms and computational capabilities offer SMEs opportunities for continuous improvement and innovation in their operations.

1.7. Section Summary and Insights

The importance of SMEs in manufacturing and the challenges they encounter in implementing I4.0 technologies have been examined. Despite facing barriers in technology adoption, SMEs remain vital to the economy of the European Union, by providing employment opportunities and contributing to job creation and growth of economics. To overcome these challenges, policymakers and stakeholders must focus on fostering technology adoption among SMEs by providing financial support, training, and technical assistance. SMEs must keep up with the process modernization and pursue the best possible outcome to stay competitive.

Collaboration with experts along with the use of maturity models can help SMEs navigate the complexities of I4.0 integration. There are many ways to perform the monitoring and check of production processes, and various engineering solutions for SMEs to embrace I4.0 have been discussed, such as IoT, CPPS, BDA, AI, and Robotics and Automation. Real-time production tracking has been identified as a transformative tool for SMEs, offering benefits like enhanced operational efficiency, quality management, and resource optimization. The implementation of the DT technology, ERP, MES, CAPP in manufacturing is crucial, but it is essential to consider the human factor in their integration for successful adoption. However, the lack of knowledge and financial resources can be a brake for the smooth implementation of these technologies.

These systems aim to increase the efficiency of manufacturing processes. The choice of the leading factors for that may vary based on the specific goals and priorities of the manufacturing company. Regularly monitoring and analyzing processes can help manufacturing organizations identify areas for improvement, set performance targets, and make informed decisions to optimize their operations and drive continuous improvement. A few examples of the most common factors for efficiency measurement can be the following: OEE, Production Output, Cycle Time, FPY, Inventory Turnover, Downtime, Lead Time, Employee Productivity, Energy Consumption, etc. By leveraging real-time monitoring, simulation, predictive analytics, and remote capabilities, SMEs can make informed decisions, enhance product development, and deliver a cost-effective and efficient production plan, which is the key to successful performance.

As described above, SMEs could be categorized as niche production where even a single piece production is possible. For such manufacturing, experts and their opinion are a leading option for decisions. However, this has side effects, such as possible mistakes, a long response time, and personal interpretations. This creates more risks for this type of companies to make wrong and time-inefficient decisions. Thus, a DSM is needed, and, based on the literature review, the focus was on creating a cost-efficient solution for the efficiency optimization of dynamic production processes in SMEs which would be based on algorithms and quasi-real-time monitoring of production.

2. RESEARCH METHODOLOGY

The research methodology shall be presented in this section. Given that the dissertation's goal is to enhance the production process efficiency through the creation of a dynamic quasi-real-time production planning method, it is imperative to undertake relevant preliminary work to accomplish the primary objectives of the dissertation. The absence of an established research methodology underscores the need for the development of a customized approach to address the specific investigational objectives. Thus, this section involves a comprehensive analysis of the chosen production sites and their alignment with the study's objectives, along with an elaboration on the DPP method offering a conceptual framework for understanding the proposed methodology. Furthermore, it encompasses the formulation of an optimization problem aimed at enhancing the production process efficiency, the establishment of a robust methodology for introducing new products into the manufacturing process, the development of a methodological approach for task prioritization within the production process, and the creation of a comprehensive methodology for evaluating and ranking employees based on their contributions and performance metrics.

The successful completion of these tasks within this section is of paramount importance as it serves as the bedrock upon which the subsequent phases of the research shall be constructed. These preparatory measures provide a solid foundation for the systematic and rigorous examination of the dynamic quasi-real-time production method and its implications for enhancing the production process efficiency.

2.1. Research Setup

The complexity of the current situation in manufacturing companies and the drawbacks of the presently existing planning tools have already been explained in literature review. This exposition serves as a prelude to the central problem statement and the envisaged resolution strategy aimed at yielding favorable outcomes. This is presented in Fig. 4.

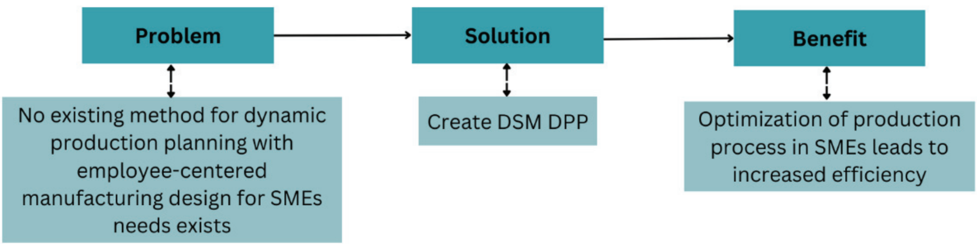


Fig. 4. Problem, solution and benefit of research

The comprehensive research workflow is depicted in Fig. 5. The initiation phase encompassed an exhaustive literature review, conducted to establish the foundation for the investigation. Despite the proliferation of diverse methodologies in the domain of production planning, no single approach has emerged as the predominant framework for planning and analysis. Furthermore, given the specific focus of this research on SMEs, a pivotal segment in the broader economic landscape, the method under development holds substantial promise for pragmatic implementation and the creation of substantial value.

Regarding the created method, the acquisition of data assumes paramount importance as it relies on quasi-real-time data. Hence, an overview of the relevant tools and technologies was conducted to ascertain the feasibility of devising an adaptable method. Existing solutions in the field were thoroughly reviewed to identify any existing gaps in production planning and to validate the novelty of this research.

Furthermore, given the basis of this research in DT technology, which encompasses algorithmic representation of production processes, a systematic review was conducted, and pertinent data was collected. The ultimate outcome of these studies is the optimization of production planning. Consequently, information pertaining to the already existing studies in this domain was presented to provide contextual background and support the development of the given approach. Several checks were done to confirm whether the collected data was truly sufficient.

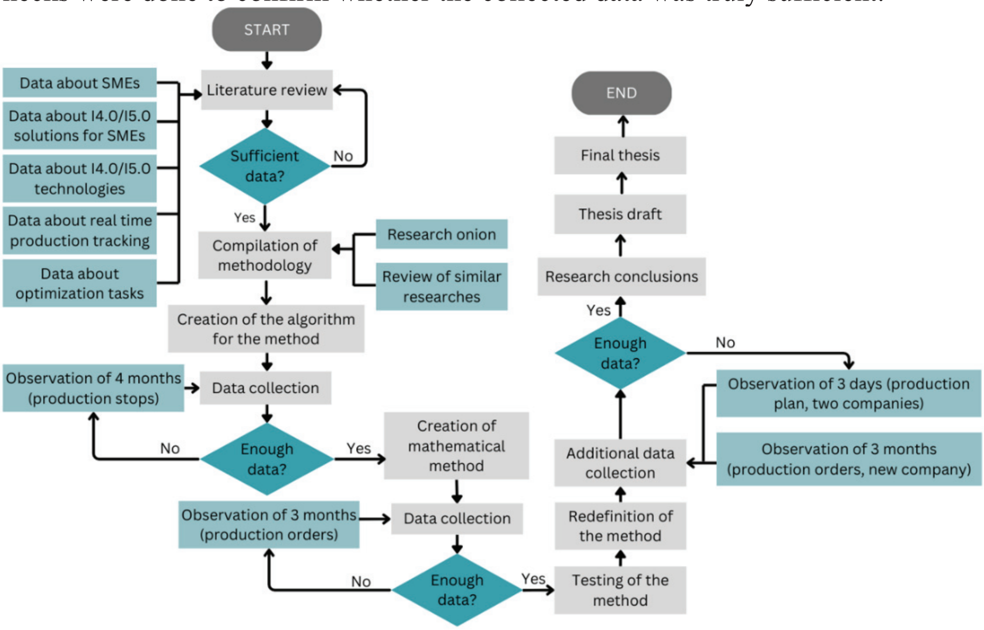


Fig. 5. Workflow of the research

Additionally, an investigation into other relevant research studies and their respective methodologies was conducted. To facilitate this process, a novel approach called *research layering* or *research onion diagram* was utilized. This graphical representation serves to visually encapsulate the salient information, thereby augmenting its accessibility and comprehensibility. The research layering diagram is presented in Fig. 6.

By building upon these foundational elements, the development of DSM was initiated, accompanied by the collection of data from the selected companies.

Systematic periodic assessments were conducted to ascertain the quality and robustness of the acquired data, thereby mitigating the necessity for supplementary validation procedures.

To establish a starting point for the method, a four-month observation period was required to gain insights into the factors causing production stoppages. Subsequently, a mathematical model was formulated based on the acquired knowledge, which was then subjected to further data collection. This second phase involved a three-month observation period, encompassing all the production orders processed during that timeframe. The developed method was checked in *Microsoft Excel* and validated by using *Matlab* software. Corrections and additional information were incorporated based on the findings from these tests.

In order to verify the reliability and applicability of the method following the aforementioned modifications, another company, which differs in size, operations, and the final product, was included in the examination process. This involved a three-month period of observation, during which, the production planning data of the company was being collected. The method was then applied to alter the production plan, and the outcomes were evaluated. On top of that, short term replanning of a 3-day workplan was performed in both companies.

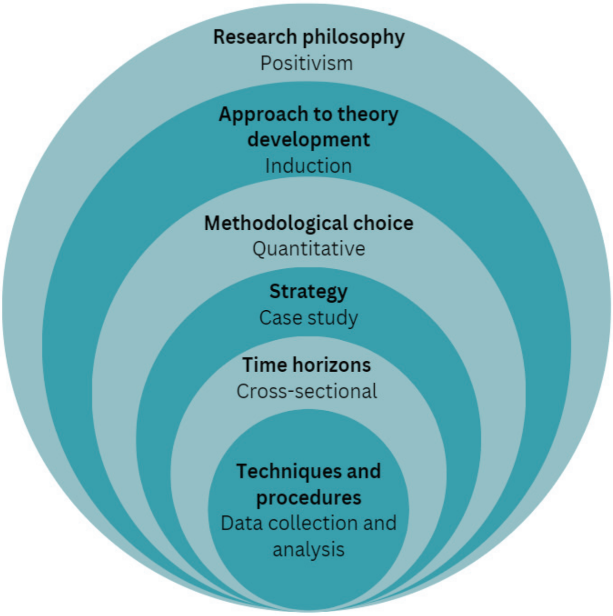


Fig. 6. Schematic model of the research

As depicted in Fig. 6, the research endeavors were grounded in the collection and analysis of data. A primary objective was to acquire real-time data and adapt the developed method to meet the specific production requirements. For the evaluation, a cross-sectional design was chosen, characterized by the collection of data from organizations at a specific moment, without longitudinal follow-up. The principal aim of cross-sectional studies is to examine relationships between variables at a singular point in time. Given the willingness of the participating companies to provide their data, a case study approach was deemed suitable instead of experimental research. Methodologically, a quantitative approach was applied, which aligns well with studies in the engineering field.

In terms of theory development, the philosophy of inquiry refers to the approach. In this case, an inductive approach was employed, wherein the research commenced with observation and data collection, followed by description and analysis, and culminating in the formation of a theory.

Lastly, the research philosophy of positivism was chosen, underpinned by the belief that knowledge can be derived through empirical observation, measurement, and the application of the scientific method. Positivism underscores the importance of objectivity, quantifiability, and the pursuit of causal relationships.

2.2. Decision Support Method[1]

DSM works continuously during the whole production process – from the time an order is placed in the system to the final steps. The main data which is needed should be provided by using different easily implemented I4.0 solutions – sensors, IoT, PID controllers, etc. Multiple data arrays are needed to facilitate the implementation of the created method. The successful utilization of this method necessitates consensus on multiple factors and the acquisition of diverse data inputs. Essential information includes employee skill sets, machine parameters, task priority rankings, and the hourly costs associated with both the machinery and the employees of the researched entity. By leveraging these data inputs, the method can autonomously make informed decisions and dynamically adjust production processes in response to interruptions. The primary objective of this DSM is to reduce reliance on human decision-making and enhance operational efficiency. The created DSM covers a wide range of disruptions which would typically require expert judgment. By minimizing human intervention, the method ensures a more streamlined and efficient decision-making process, thereby reducing the potential for errors and delays. It employs data-driven insights to independently evaluate and respond to production stops, while offering timely and optimal solutions. As the target group for this method is SMEs where dynamics in the production is a standard case, thus DSM must be adapted to quickly changing and unpredictable situations. Based on this, DSM will support DPP. The aim is to maximize the production efficiency and minimize the negative effect of disruptions by relying on algorithmic analysis rather than relying solely on human expertise.

2.3. Dynamic Production Planning[2]

The primary objective of DPP is to dynamically adjust the production sequence in quasi-real-time. This methodology is specifically designed for SMEs which do not engage in mass production or use innovative production planning strategies. However, such enterprises commonly operate in a rapidly changing environment, where the

[1] The material in this section has previously been published in [138]
[2] The material in this section has previously been published in [138]

production of niche or custom-made orders is prevalent. Additionally, these companies often rely on a workforce which places emphasis on employee-centric practices, thus adding further complexity to the planning process. The most frequently encountered production issues and disruptions in this context include machinery failures, material shortages, quality issues, the introduction of new products, and employee absence. DPP addresses all of these areas. Production in such companies commonly relies on human workforce. This adds even more possible scenarios to everyday planning, and the overall production cycle can be presented as in Fig. 7. Companies must understand that failure of machinery might be predicted or prevented with regular monitoring. Lack of materials can be avoided with agreed buffers, or new product implementation can be solved with specific generalization of operations. However, the part of employees is totally unpredictable. There are too many possible cases for the absence of employee(s), such as pandemics, accidents, personal reasons, disagreements between co-workers, etc. Thus, flexibility to change workers based on their skills is a new practice which is not involved in the regular production planning systems.

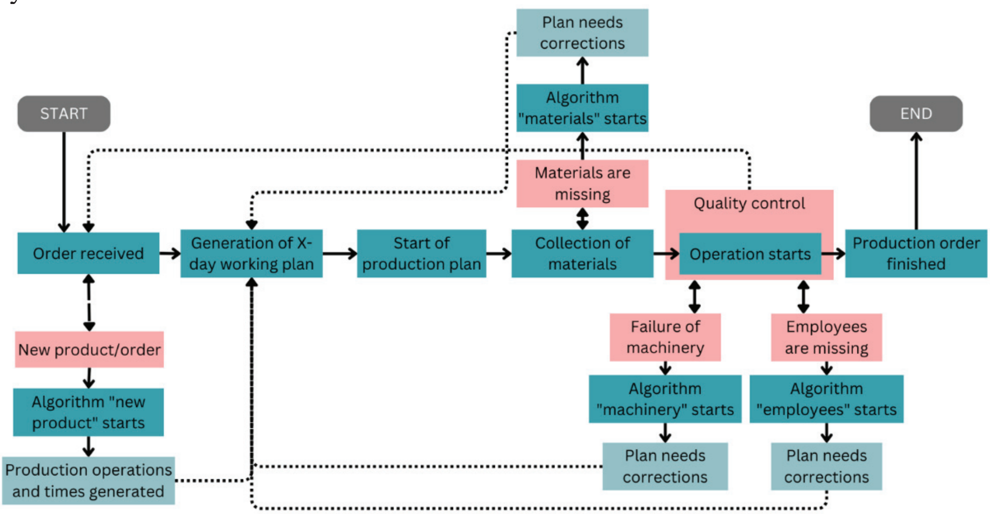


Fig. 7. Representation of a production cycle

Those parts in Fig. 7 which are marked in red are solved with the created method. Consequently, the overall production time is reduced, as the DSM DPP now handles the commonly occurring interruptions. The ability to obtain calculated and evaluated solutions within seconds enables companies to proceed with minimal deviations in the production. Extensive testing of this method in various production companies has demonstrated its adaptability and versatility. By employing this approach, it was observed that the same production time yielded higher production output. In other words, the stand-by time is minimized and converted into active production time.

2.4. Overview of Researched Production Sites

The present research study focuses on SMEs. This sector shows tendency to grow, if comparing statistics from several years. 36% growth of such enterprises during the period of 2014–2022 was observed in Lithuania, while the EU experienced 13% growth [130, 131]. The number of SMEs during this time period is presented in Fig. 8 (Lithuania) and Fig. 9 (EU).

Fig. 8. Number of SMEs in Lithuania (2014–2022)

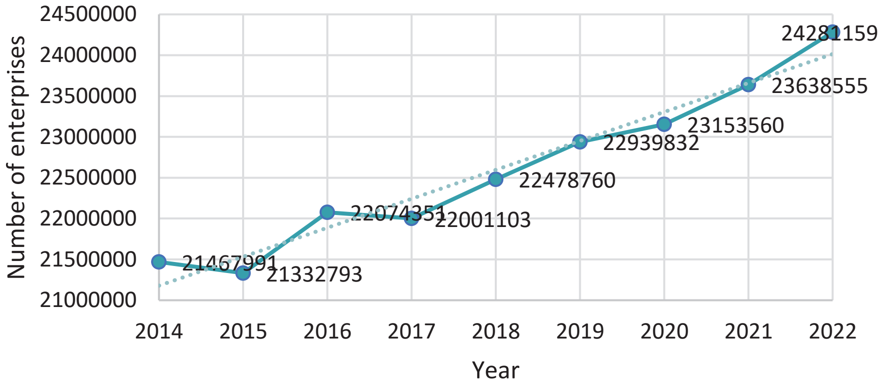


Fig. 9. Number of SMEs in EU (2014–2022)

Consequently, the selected observed companies had to conform to the criteria of being an SME type enterprise. Both of them were operating in the manufacturing domain. Due to emphasizing the significance of the manufacturing industry, it was given priority during the observation phase. Notably, two distinct companies willingly participated in the study by providing the relevant information and agreeing to undergo monitoring. Different companies were selected specifically to understand the limitations of the method and its versatility. These companies are denoted by differences; thus, such a decision of facilitating an evaluation of the adaptability of the developed method was made on purpose, thereby providing an opportunity to assess its effectiveness across multiple organizational contexts. Both companies shall be described below, in Subsections 2.4.1 and 2.4.2.

2.4.1. Metal processing Company (A)

The initial research was conducted in a metal processing company located in Lithuania, which was employing a total of 75 individuals during the study, thus being classified as a medium-sized enterprise. This company specializes in the production of furniture components, including metal tube legs, brackets, frames for shelves, tables, and various other items [132]. They maintain an inventory of over 500 different product variations to accommodate customer demands, as illustrated in Fig. 10, which highlights the company's most frequently produced items. Notably, they accept small or custom sample orders and offer a range of metal processing services. The nature of their production varies daily, which emphasizes the importance of flexibility, rapid response, and adaptability. This company is part of a larger group comprising more than 20 entities, and serves as a supplier to both its group members, and various other companies across Europe. Given that their end products are utilized by other manufacturing firms, any delays in delivery are deemed unacceptable, as they could disrupt production processes at these downstream companies. Consequently, precision and accuracy are of utmost importance in this business model. It is worth noting that, at the time of the research, the entire production equipment was being operated by human employees, and there were no robotic or automated production lines in place.

In this organization, production monitoring was taking place since 2020 to 2023. Several months of production order data were used to perform targeted evaluations. Precise observations were carried out during the period of November and December in 2022, with the entire observation spanning over a duration of 3–4 months. The objective behind this effort was to gain insights into and verify the primary emerging issues, while assessing the above explained methodology. The company willingly supplied the necessary data and consented to the implementation and testing of production planning based on the newly devised method. The company recognizes the necessity for alterations in their production planning and is considering the imminent adoption of such a tool. Diverse data sets were collected to maximize the information available for investigative purposes, thus encompassing data from every shift, every operation, and every product produced.

As for the start, workflows had to be created. To create algorithms and check the program, a product and its operations were selected. Starting from a product, it was easier to understand problems in the production and adapt in the method, while the plan was to evaluate the created method in another company later on so that to check its universality.

Company A conducts 13 main technological operations which were involved in the whole examination process:

1 – manual cutting with a belt saw machine;
2 – manual cutting with a disc saw machine;
3 – automatic cutting;
4 – bending;
5 – manual grinding;
6 – automatic grinding;

7 – turning;
8 – drilling;
9 – punching;
10 – welding;
11 – finishing in a full-size painting booth;
12 – finishing in a small-size painting booth;
13 – packaging.

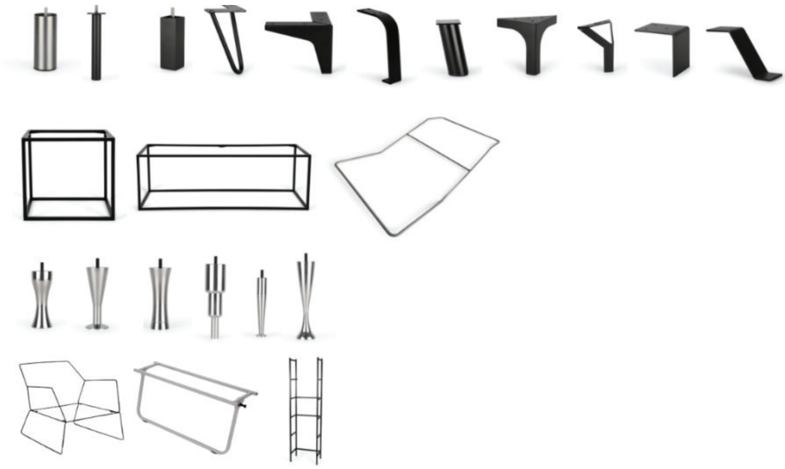


Fig. 10. Products of Company A

It should be highlighted that Company A performed other operations as well, such as CNC milling, or wood turning, but those were not involved during the check of the method, and thus they are not listed, and those operations were not involved in the skills evaluation, either.

2.4.2. Automotive body repair Company (B)

As the second enterprise, an automotive body repair company was chosen. Established in 2018 and situated within the geographical confines of Lithuania, this company boasted a workforce numbering six employees, thereby falling within the classification of a small-scale enterprise. The variance in the business profile compared to the previously elucidated Company A lends valuable insights into the potential adaptability of the proposed methodology across diverse industry sectors.

The main technological operations in this company are nine in number, and they are listed below:

1 – disassembling;
2 – geometry restoration;
3 – welding;
4 – grinding;
5 – covering;
6 – finishing;
7 – assembling;

8 – polishing;

9 – cleaning.

The data was collected through direct observation of the company's operations – which are nine different operations without the use of automatic solutions. The company was operating in one shift of eight hours, with all the employees working simultaneously. As this company does not produce the final product, but still provides manufacturing services, all of its operations were involved in the observation since none of its service could have been specifically taken from others.

The main characteristics of both companies are presented in Table 1.

Table 1. Characteristics of companies A and B

	Company A	**Company B**
Type	Medium-sized enterprise	Small-sized enterprise
Total number of employees	75	6
Final outcome	Product, service	Service
Industry	Furniture	Automotive
Number of operations	13	9
Number of machinery	17	14
Working shifts	2	1
Established	2005	2018
Sales revenue 2022	2,500,000 Eur	50,000 Eur
Location	Lithuania	Lithuania

2.5. Variables in Production Planning

The first thing to understand of SMEs is that they face different disturbances each moment in the production. Thus, the most common variables in production should be found and confirmed. This allows concentrating on the most important production issues.

The key elements of SMEs are employees, machinery, materials – and any deviation in one of these fields follows with a production delay. However, it is a good practice to check and confirm the main reasons of stops in production by monitoring its processes. In order to confirm that in this research, a monitoring was made of production processes which lasted for 4 months – from January to April, 2022. As shown in Fig. 11, the absence of workers was a leading problem during all 4 months. In the second place, there was a delay of components, or other sourcing failures. The third problem was the failures of machinery. Meanwhile, the final section was changes in orders, and, more specifically, changes originating from the customers. This section is not controlled by the company itself; so, it was not further researched or investigated. Based on these numbers, the created method solves these top three issues [132].

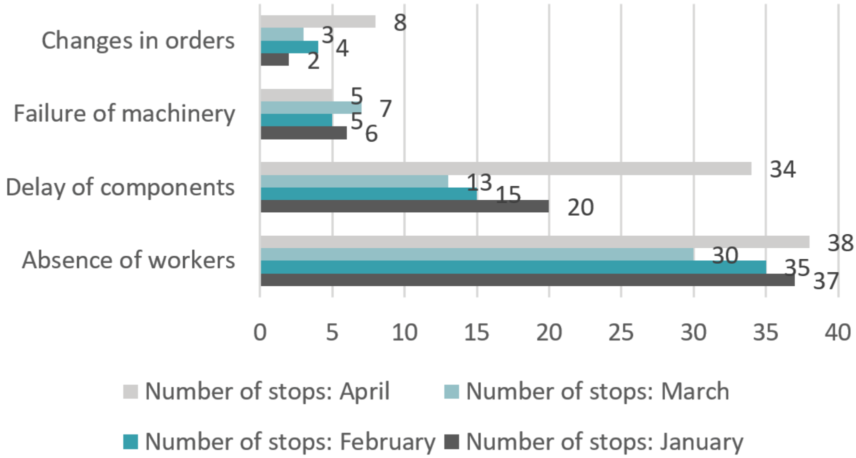


Fig. 11. Monitoring of production stops in Company A from January to April, 2022

The described issues are directly solved with the created method, however, a proper production plan gives additional benefits, such as an increased profit, possibility to be more competitive thus lowering prices, reducing electricity consumption or CO_2 emissions, increased quality, etc.

2.6. Criteria Selection for Production Planning

This study aims to develop a method based on a mathematical model to enhance the efficiency of production processes. The optimization of production efficiency is of paramount importance to companies, as it directly impacts the overall time required to manufacture products. The ability to use production resources in the most efficient way has a direct impact on the financial performance and resilience of organizations. Consequently, any wastage of time, resources, or energy must be minimized. The primary objective of this research is to create an efficiency optimization function which would minimize the production time and maximize the profit. This function incorporates multicriterium evaluation and is based on linear programming. By employing DSM DPP, this study addresses the challenge of selecting the optimal production option from several possibilities, thus ensuring that the agreed-upon values are maximized.

The need for production efficiency arises from the inherent desire to reduce the wastage of time, resources, and energy. Inefficient production processes can result in increased costs, missed delivery deadlines, and reduced customer satisfaction. Therefore, it is crucial for companies to identify and implement strategies that would streamline their operations and eliminate any bottlenecks hindering production efficiency.

This study presents a methodological approach which considers multiple factors critical for ensuring effective selection in production companies. Given the presence of multiple operational centers within every company, it is common for employees to lack the requisite skills to operate all types of machinery. To address this issue, a skills matrix is the central component of the employee allocation process. Initially presented as a visual representation (Fig. 12), the matrix aids in identifying the skill levels possessed by individual employees, and thus facilitating the knowledge of their respective roles in the operation. Consequently, in the event of an employee's absence, this visual representation proves invaluable in identifying suitable replacements. While the matrix in Fig. 12 serves as a visual aid, it is further operationalized as a data array within the method.

This method operates on readily available data, requiring minimal modifications in production processes or data acquisition. However, it necessitates essential product data, specifically, the operation times and sequence. Considering the context of SMEs, a significant portion of production involves unique or one-time orders, potentially constituting niche products. Consequently, these companies often lack the predetermined operation times for such products, thus rendering the created method incapable of evaluating their production. To address this issue, this research explains a product segmentation approach and presents algorithms and examples to illustrate its implementation.

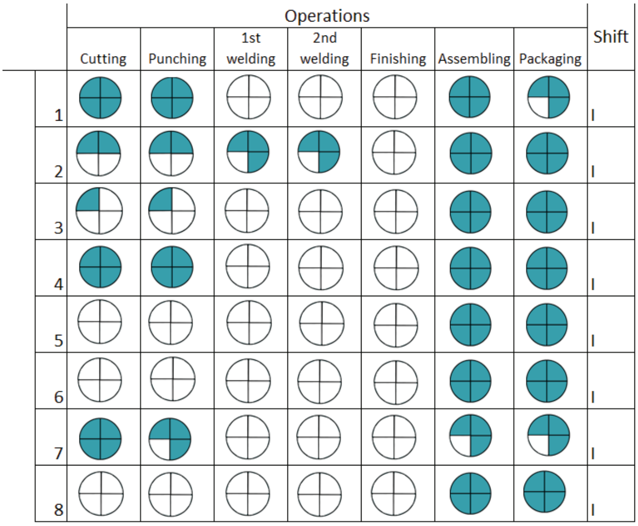


Fig. 12. Visual presentation of the matrix of skills

Moreover, in production environments, multiple tasks often occur simultaneously, thus making it inherently subjective to determine their relative importance. Consequently, DSM DPP necessitates the incorporation of factors for production ranking, along with various degrees associated with each factor. This enables the evaluation of production processes based on the most pertinent information specific to the production context. These factors are selected within the company, and each of the factors is assigned a coefficient to highlight their importance.

2.7. Section Summary and Insights

Observations showed that SMEs have dynamic production, and, in general, they encounter a few main problems: failure of machinery, delay of components, and absence of employees. Two different manufacturing companies were involved in this research, and they have different products, numbers of employees, operations, etc. However, for both of them, it is important to a have virtual assistant to manage the quickly changing course of production. Thus, the DSM DPP method covers the dynamic production environment and replanning of production orders in the most efficient sequence which is created based on the optimization function. It is multi-criterion evaluation with such factors as the task importance, the matrix of employees' skills, etc. This method does not require additional resources for its adaptation. Checking it in two different companies presents its adaptability and versatility. When using this method, the main objective is to save the overall production time by reducing the ineffective (passive or stand-by) hours and thus increasing the production profit. As the following benefits, optimum usage of resources solves environmental problems, proper selection of employees ensures a higher quality level and a lower amount of scrap. DSM DPP is a solution for dynamic replanning without requiring additional financial or knowledge resources.

3. DEVELOPMENT OF DECISION SUPPORT METHOD AND THE DEVELOPED MATHEMATICAL MODEL

3.1. Introduction

Small and medium-sized engineering production enterprises encounter obstacles associated with the unforeseen and swift fluctuations in the availability of labor, materials, and equipment. These challenges pose difficulties for companies specializing in unit or batch production and engaging with customers who demand short lead times. To gain insights into the prevalent issues and devise a resolution in the form of a computerized DSS, a comprehensive investigation should be conducted. Such production requires periodical check to notice in time the likely or already inevitable stops. A new method is needed which could be easily adapted and would not need specific knowledge for data. Employee-centered companies not only use human power for their main operations but also use expertise opinion to agree on decisions. This can lead to a delay in response, personal selection, lack of knowledge or information. Thus, it is not only needed to modernize production and its data collection, but also to the decision-making level to avoid mistakes where the production manager is the key person. This new method presents a matrix of skills which evaluates human knowledge in each operation. To the best of the knowledge of the author of this thesis, such a method still cannot be found in any other research. Based on literature review [134–136], a variety of production planning methods, such as Data-driven decision support tools, or DT-driven real-time planning, can increase production efficiency in the range of 5–8 %. Following this, the new method should present results in this interval.

3.2. DSM DPP Algorithms

With this information about the most problematic production areas, the new method generates 3 algorithms:

1. 'Employees' algorithm which covers the absence of employees, and their reorganization between tasks (Fig. 13).
2. 'Machinery' algorithm which covers the failure of machinery and replans production (Fig. 14).
3. 'Materials' algorithm which finds a solution in case some materials are missing, and the original production plan cannot be followed anymore (Fig. 15).

These three components are essential for any production. Observations were made for a metal processing company and for an automotive body repair company, and these categories were shared by both spheres. In this research, the employees algorithm is mostly described and presented, since the other two algorithms follow the same idea. This was decided based on the novelty of employee skills and absence implementation in production replanning.

A concise overview of the workflow of the employee algorithm is outlined in Fig. 13. The general steps can be summarized as follows.

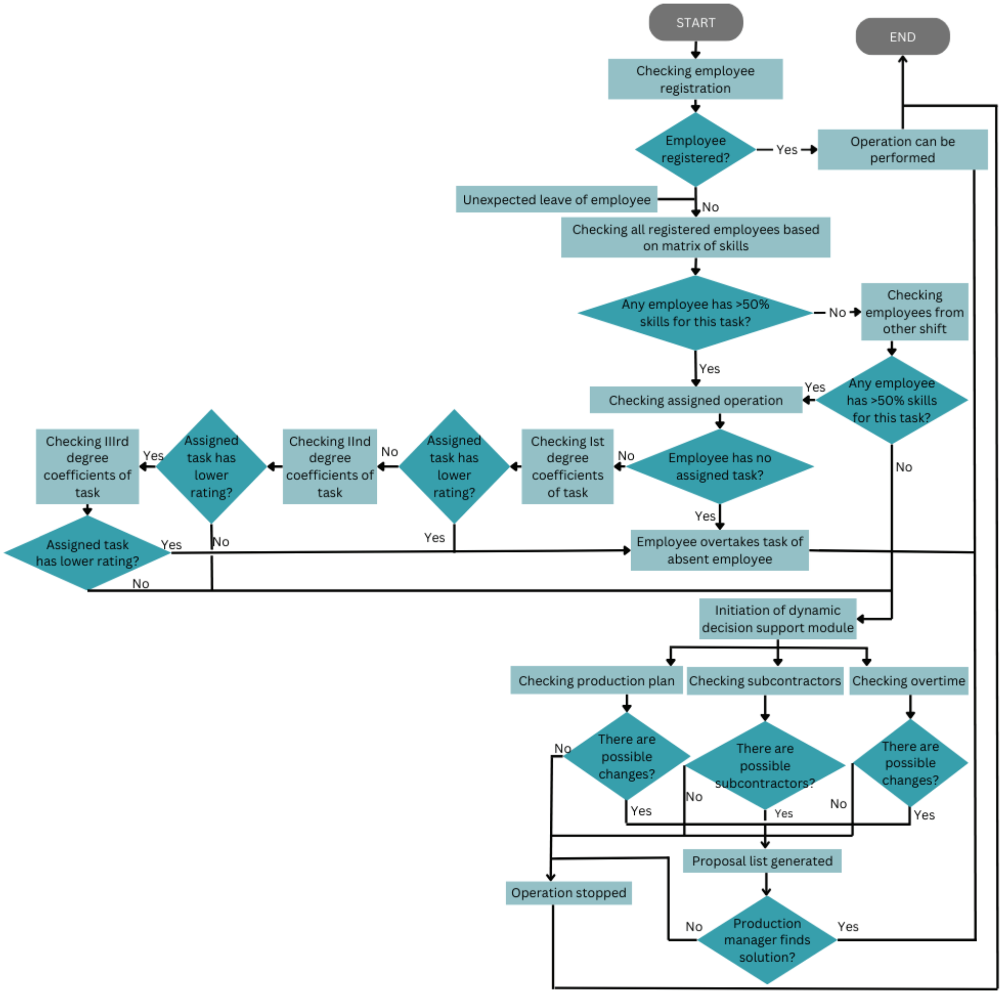


Fig. 13. DSM DPP algorithm for the employees section

Step 1: Automatic registration of employee attendance and departures occurs through the use of personal cards. The system receives information about the employee, including their name, surname, and the timestamps for check-in and check-out. The system is human-centered, and it checks the availability of human resources.

Step 2: In the event that the system indicates about a missing required human resource, it automatically proceeds to the subsequent stages requiring the utilization of a skills matrix.

Step 3: The algorithm examines whether any employees within the same shift possess more than 50% of the skills required for the operation of the absent employee. Initially, this assessment is conducted among the employees working in the same shift. However, if no suitable replacements are found within the shift, the system extends its search to employees from different shifts, if available. It is a universal algorithm, thus this part with another shift might not be familiar to all companies, and thus the algorithm would be adapted during implementation. However, sometimes, there might be no 'several shifts' in the company, but rather different production sites of the same company, and this might be evaluated as well. Also, the number of shifts might vary between seasons; so, this part of the algorithm would be adapted according to the need.

Step 4: A successful outcome occurs when the system has identified an employee with the requisite skills who is not currently engaged in any assigned tasks. In such cases, the replacement process is initiated, and the task is carried out. However, there are instances where a skilled employee may have an ongoing task. In such situations, the system proceeds to conduct a three-stage evaluation process to determine which task takes precedence – the one the employee is currently performing, or the task without an assigned employee. This evaluation necessitates the consideration of various factors, which must be defined and agreed upon within the company. Additionally, values and coefficients for these factors should be established and confirmed for all orders.

Step 5: Based on the need for three-stage evaluation, each company has to select several factors of production importance. These factors might be the following:

- delivery date;
- the need of this task (technological operation) for further production processes;
- quantity;
- clients ranking;
- extra requirements (i.e., it is sample order for large quantities to be (likely) ordered in the future; parts should be sent to a subcontractor; etc.) [132].

Step 6: Table 2 presents what is required to evaluate the importance of a task. Each factor has its value from '0' to '1', where values closer to 1 are most important, and the degree of importance is therefore ranked in a quantifiable manner. Each factor should be categorized in groups of most important factors (Ist degree), less important (IInd degree) factors, which are evaluated if the Ist degree was not sufficient, and, lastly, IIIrd degree factors which basically should be something specific and unique what would change the situation. This selection is individual for each factory, and should be discussed before the beginning of the method implementation. As an example, the factors could be the delivery time, the quantity of an order, the clients positioning, sample production, etc. It is recommended to focus on only the most important factors, thus keeping two Ist degree and IInd degree factors, and only one IIIrd degree factor. The presently given factors and the number of them are based on experience in the researched companies since they were shared by both of them. However, it is a recommendation, and they might be selected freely in the course of the adaptation of the method.

Table 2. Task importance assessment factors

Factor value	**Value for task**	**Degree**
Factor 1 (f_1)	V_1	1
Factor 2 (f_2)	V_2	...
Factor 3 (f_3)	V_3	...
...	...	...
Factor n (f_n)	V_n	3

The formula to compute each coefficient value v is expressed as:

$$v = \sum f_n \cdot V_n, \tag{1}$$

where: V_n – the value of a factor for the specific task;

f_n – the factor value [132].

To evaluate their importance, factors of the same degree level should be summed up. Then, overall, Ist, IInd and IIIrd degree factors would be compared. As shown in Fig. 13, if the Ist degree coefficient is higher for the task which would not be in process due to the absence of an employee, then, the available employee would be assigned with it. If not, the evaluation of the IInd degree is initiated, and, if needed, the IIIrd degree is evaluated as presented.

Step 7: However, in real-world scenarios, there may arise a situation where no employee is available or sufficiently skilled to execute the necessary production reconfiguration. In such instances, the algorithm activates the Dynamic Decision Support (DDS) module. Within this module, a comprehensive assessment of additional external data takes place to formulate a proposal. For instance, if there is a lack of available employees to fulfill the required tasks, the DDS module examines potential alterations in the production orders, the availability of subcontractors, and the feasibility of overtime options. To ensure the effectiveness of this process, it is imperative for a company to import all pertinent data, including contact information, working hours, and lead times from subcontractors. This enables the system to autonomously determine whether a viable solution exists or not.

Step 8: The system either stops operation or finds a solution.

The same logic is used for the other two algorithms, i.e., machinery (Fig. 14) and materials (Fig. 15). Only a slight difference is observed since the matrix of skills is not needed for these algorithms, and it is replaced by data arrays containing merely the principal information pertaining to machinery or materials. Notably, these data arrays do not have a hierarchical layering of applicability.

The described steps could be followed for these algorithms as well as there are only a few minor differences between the algorithms. Thus, testing one of them gives the overall understanding of the other algorithms and their validity.

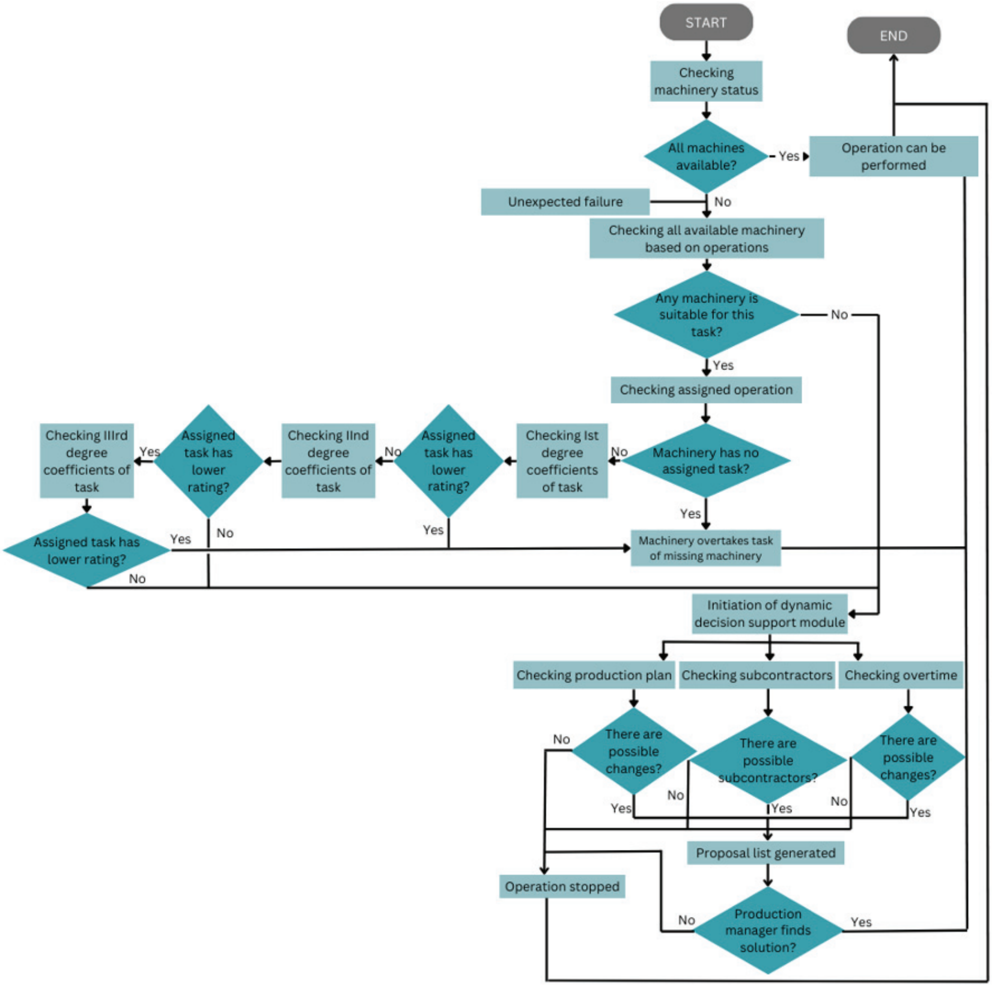


Fig. 14. DSM DPP algorithm for the machinery section

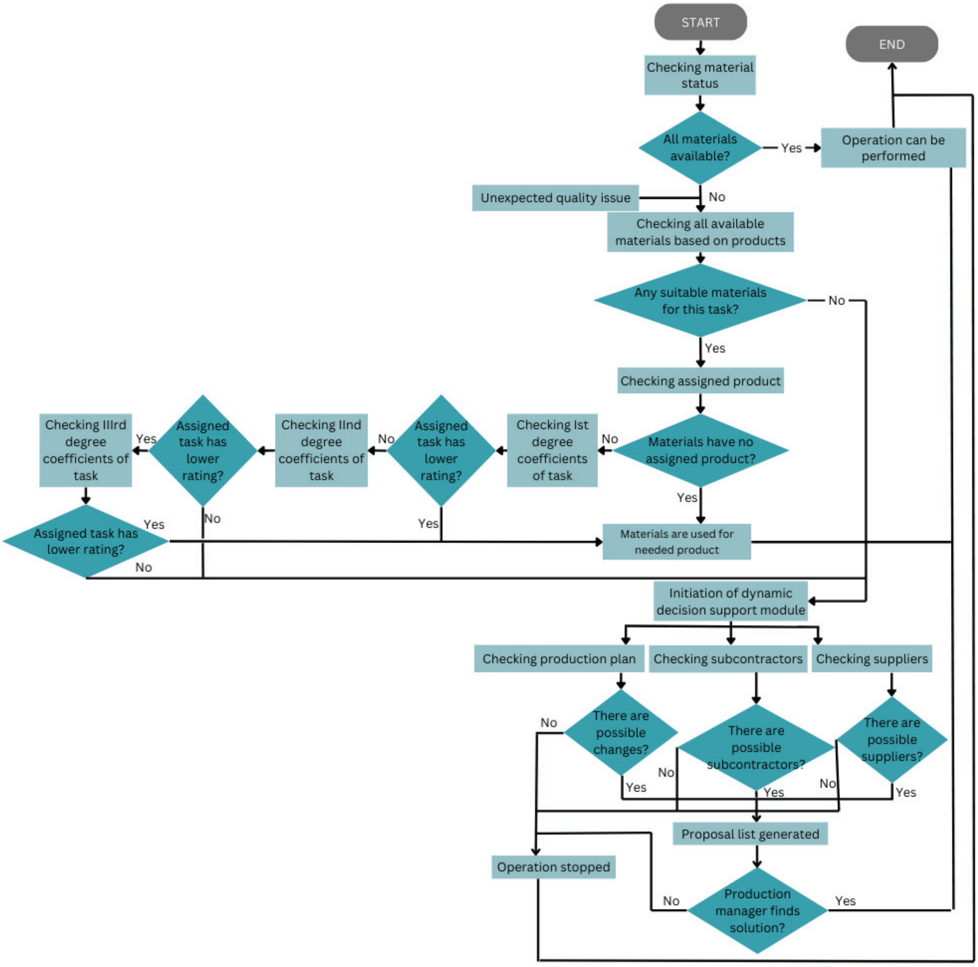


Fig. 15. DSM DPP algorithm for the materials section

3.3. Mathematical Model[3]

The start of DSM DPP is to describe algorithms, and then the mathematical model follows. To test this method in a program, mathematical transformation of presented algorithms has been done, and it shall be described in this subsection.

The mathematical model starts with the creation of the initial day plan. Matrix P1 stands for the initial day plan:

$$P1 = (p1_{ij}), i = \overline{1,k},\ j = \overline{1,6}, \qquad (2)$$

where: k – the number of employees;
i – the number of rows;

[3] The material in this subsection has previously been published in [132]

j – the number of columns.

Another matrix M is needed which presents the status of materials:

$$M = (M_{ij}), i = \overline{1, x},\ j = \overline{1,6}, \qquad (3)$$

where: x – the number of materials;

$M_{i,1}$ – quantity of the material in stock;

$M_{i,2}$ – the required quantity of the material for the order;

$M_{i,3}$ – the quantity of the material already used in the production;

$M_{i,4}$ – the quantity of the material in defective products.

It is always checked and calculated if there is enough material for the order:

$$M_{i,5} = M_{i,1} - M_{i,3} - M_{i,4}; \qquad (4)$$

$$M_{i,6} = \begin{cases} 0, M_{i,5} < M_{i,2} \\ 1, M_{i,5} > M_{i,2} \end{cases}. \qquad (5)$$

The respective elements within the columns of matrix P1 can assume specific values as follows:

$$P1_{i,1} = \begin{cases} 0, equipment\ is\ not\ available \\ 1, equipment\ is\ availabe \end{cases}; \ (6)$$

$$P1_{i,2} = M_{i,6}; \qquad (7)$$

$$P1_{i,3} = \begin{cases} 0, no\ task\ is\ assigned \\ 1, task\ is\ assigned \end{cases}. \qquad (8)$$

The fourth column displays the assigned task number. Consequently, m represents the count of distinct production orders processed during this shift:

$$P1_{i,4} = \overline{1, m}. \qquad (9)$$

The fifth column contains the operation numbers. Here, n denotes the count of various production operations:

$$P1_{i,5} = \overline{1, n}. \qquad (10)$$

The final column represents the employee count, denoted by k, signifying a particular numerical value:

$$P1_{i,6} = \overline{1, k}. \qquad (11)$$

The initial plan verification involves confirming the attendance of all employees, while simulating real-life conditions. This data input results in the creation of a new matrix denoted as S:

$$S = (s_{ij}), i = \overline{1, k},\ j = \overline{1, 4}. \qquad (12)$$

The elements within the columns of matrix S can assume specific values as follows:

$$S_{i,1} = \begin{cases} 0, employee\ is\ absent \\ 1, employee\ is\ working \end{cases}. \quad (13)$$

Another verification step involves determining whether an employee is capable of commencing a new operation, which entails ensuring the availability of materials, properly functioning equipment, and an initial task assignment. To conduct this assessment, data from matrix P1 is utilized:

$$S_{i,2} = P1_{i,1} \cdot P1_{i,2} \cdot P1_{i,3} = \begin{cases} 0, employee\ cannot\ work \\ 1, employee\ can\ work \end{cases}. \quad (14)$$

The third column of matrix S indicates whether the planned task has been executed. Even if $S_{i,2} = 1$, but $S_{i,1} = 0$, it is not feasible to carry out the task, as the assigned employee is not present at work:

$$S_{i,3} = S_{i,1} \cdot S_{i,2} = \begin{cases} 0, task\ is\ not\ performed \\ 1, task\ is\ performed \end{cases}. \quad (15)$$

The fourth column is for the final result value:

$$S_{i,4} = S_{i,1} + S_{i,3} = \begin{cases} 0 \\ 1. \\ 2 \end{cases} \quad (16)$$

A final result of '1' indicates that the employee is on stand-by, a result of '2' signifies that no changes are required, and if the result equals '0', further assessment is necessary to determine if it is also '0' (no actions are necessary), or '1' (replacement is required).

Following this process, matrix C is generated, with the respective elements within its columns capable of assuming specific values:

$$C_{i,1} = \overline{1,k},\ j = \overline{1,n}; \quad (17)$$

$$C_{i,2} = S_{i,4}; \quad (18)$$

$$C_{i,j} = \begin{cases} 0 \\ 0{,}25 \\ 0{,}5 \\ 1 \end{cases}. \quad (19)$$

The assessment of task rankings is underway, which results in the formation of the matrix OW. The columns in the OW matrix can take on distinct numerical values.

$$OW_{i,1} = \overline{1,m}. \quad (20)$$

From the second to the n^{th} column, the values of factors are given:

$$OW_{i,2} = \overline{0{,}1}; \quad (21)$$

$$OW_{i,3} = \overline{0{,}1}; \quad (22)$$

$$OW_{i,4} = \overline{0{,}1}; \quad (23)$$

$$OW_{i,5} = \overline{0,1}; \tag{24}$$

$$OW_{i,n} = \overline{0,1}. \tag{25}$$

Then sum of the Ist degree is presented:

$$OW_{i,n+1} = OW_{i,2} + OW_{i,3}. \tag{26}$$

The sum of the IInd degree is presented:

$$OW_{i,n+2} = OW_{i,4} + OW_{i,5}. \tag{27}$$

The sum of the IIIrd degree is presented:

$$OW_{i,n+3} = OW_{i,n}. \tag{28}$$

If

$$OW_{y,7} > OW_{i,7}, \tag{29}$$

where *y* is the absent employee and *i* is the employee who covers this task and whose $S_{i,4} = 2$.

In such a scenario, the decision is that employee *i* will replace employee *y*.

However, if not, a second-degree check is initiated:

$$OW_{y,8} > OW_{i,8}. \tag{30}$$

In this situation, employee *i* replaces employee *y*. If not, the DDS process is initiated.

The verifications have successfully confirmed the correctness of the algorithm in addressing the issue of employee absences. The results obtained from the *Matlab* program experiments shall be detailed in the following Subsections 4.3 and 4.4.

3.4. Dynamics in Production Planning

Production follows several steps during which any unpredicted problems can occur. Many outside factors can impact and create disturbances which have to be solved. To do that, DSM DPP is created, and it solves employee-centered production problems.

The presented algorithms solve employees, machinery, and materials problems. However, going deeper into the method, the main DSM DPP idea is to update the production plan in the real time, and the updates would take place with the help of algorithms.

To activate the developed method, it is essential for each production order to possess specific initial data which must be mutually agreed upon prior to the method activation. Although all the information is crucial, the foremost objective is to consistently remove superfluous and inconsequential values. The process involves a careful assessment so that to identify the parameters which exert the most significant influence on the order sequencing. If it becomes evident that certain parameters have no discernible impact, they are systematically excluded from consideration.

Through the application of regression analysis, those columns of data that exhibited statistical insignificance and lacked influence were singled out. Regression analysis serves as a tool for exploring the connections among multiple variables. Its primary purpose is to scrutinize how a dependent variable is impacted by one or more independent variables. This analytical technique aids in gauging the strength and direction of the relationships between these variables and allows for predictions regarding the dependent variable based on the independent variable values [137]. In the process of selecting criteria, a confidence level of $p < 0.05$ is established, which guides the identification of factors that can be disregarded in each instance [132].

The time of operations and their sequence is mandatory information to initiate this method. Thus, one of the 'stop' reasons in the production circle could be missing information of some first-time production. However, in order to consider this method as suitable for SMEs which tend to produce small batches, niche products or custom orders, it is necessary to present assistance for this obstacle of lack of information. Fig. 16 presents an algorithm for a new product. The system follows it when there is no input information about operations.

As shown, products are divided into categories, each of which has its own complexity level. As a final result, the operation times and processes will be assigned based on some agreed values.

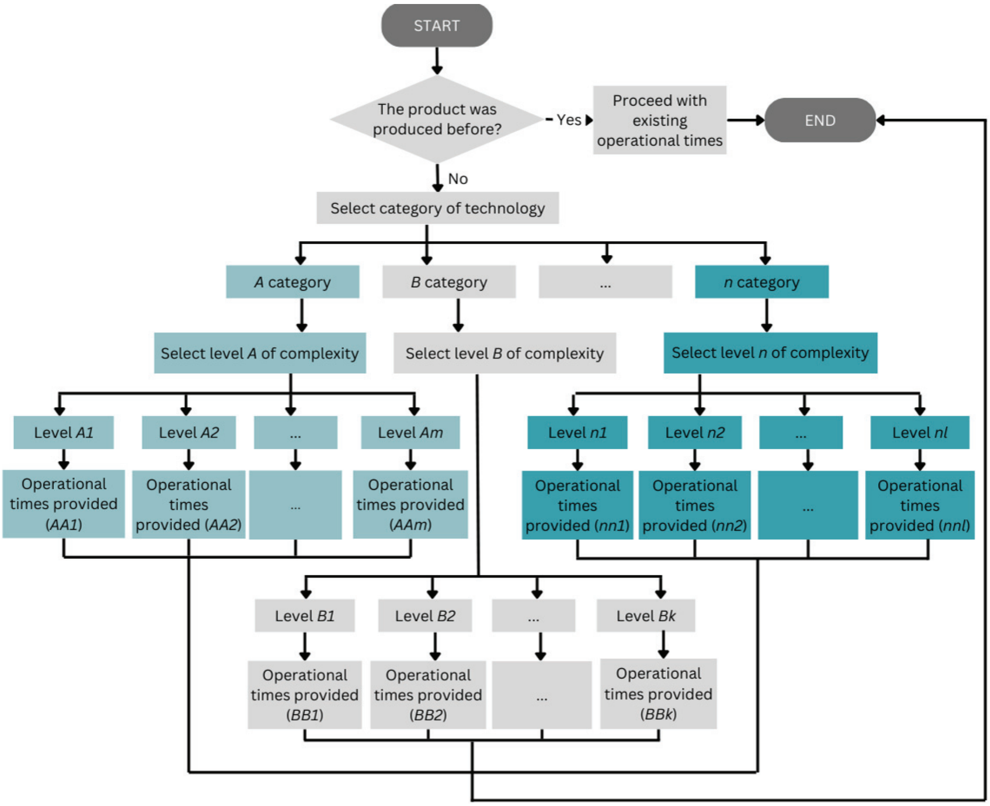


Fig. 16. DSM DPP algorithm for new product implementation

3.5. Employee-Centered Production

This research is oriented to SMEs which habitually follow the employee-centered company model. Even operations which do not require specific knowledge are performed by employees. Such operations can be performed by the majority of personnel, thus the ability to find a replacement – if needed – is very high. On the other hand, when performing specific tasks, such as welding, and CNC operations, highly specific skills are needed, and the company might have problems if they do not have more than one specialist. For this reason, the matrix of skills is involved in the method. However, there are cases when SMEs use robots, cobots or semi-automated working space in the production. Based on their category and capability – fixed or collaborative – such machinery can perform different tasks and, in some cases, cover employees, whereas, in other cases, machinery is covered. Based on this, algorithms of employees and machinery would be impacted with additional possible solutions. The adapted employees algorithm is presented in Fig. 17.

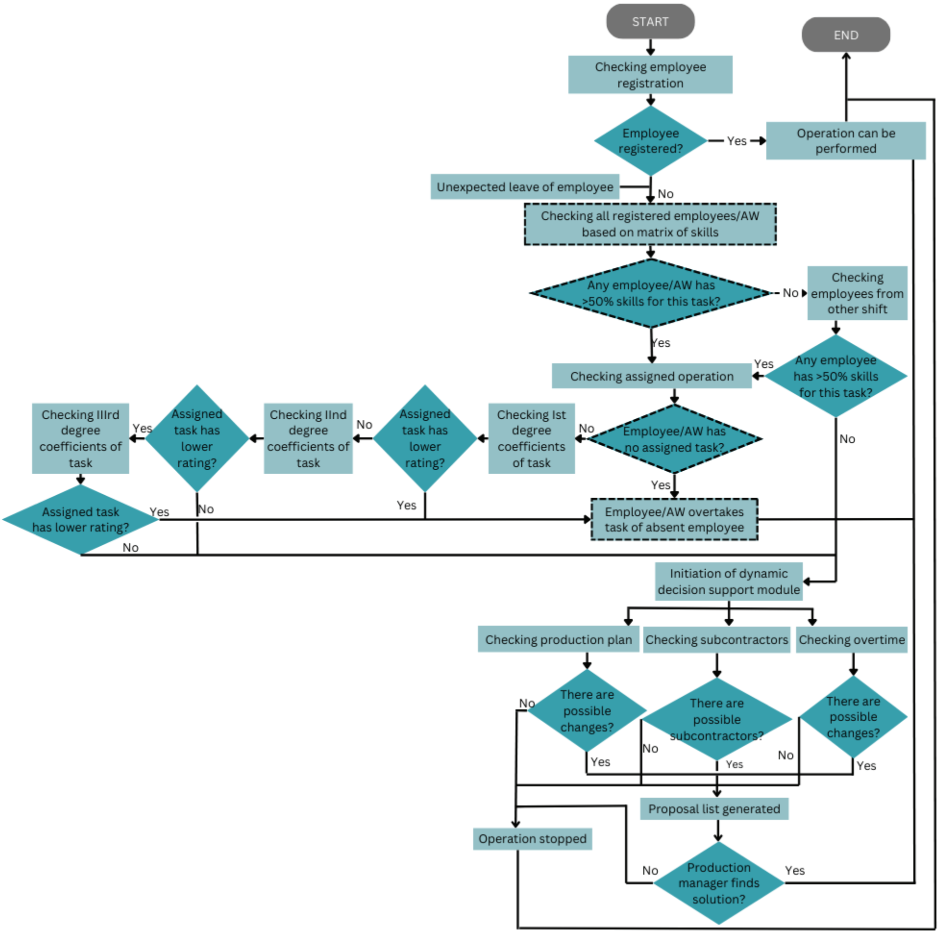


Fig. 17. DSM DPP algorithm for the employees section when the company has an available automated machine

There would be a need for an additional check whether this automatic solution can replace machinery or an employee. Having an automatic work cell which could perform the same tasks as an employee, the matrix of skills should also be complemented with such an automatic 'employee' and its skills. The same should be done with the machinery section – as the new 'machinery' would be involved in the evaluation.

Having an automatic workplace (AW) which could only do specific operation, it may be used for other products processes, but then it would be fitted in the machinery data field with its own capabilities, by which the possibility to use it in operations would be evaluated. The machinery algorithm for a company with specific cells would look like the model depicted in Fig. 18.

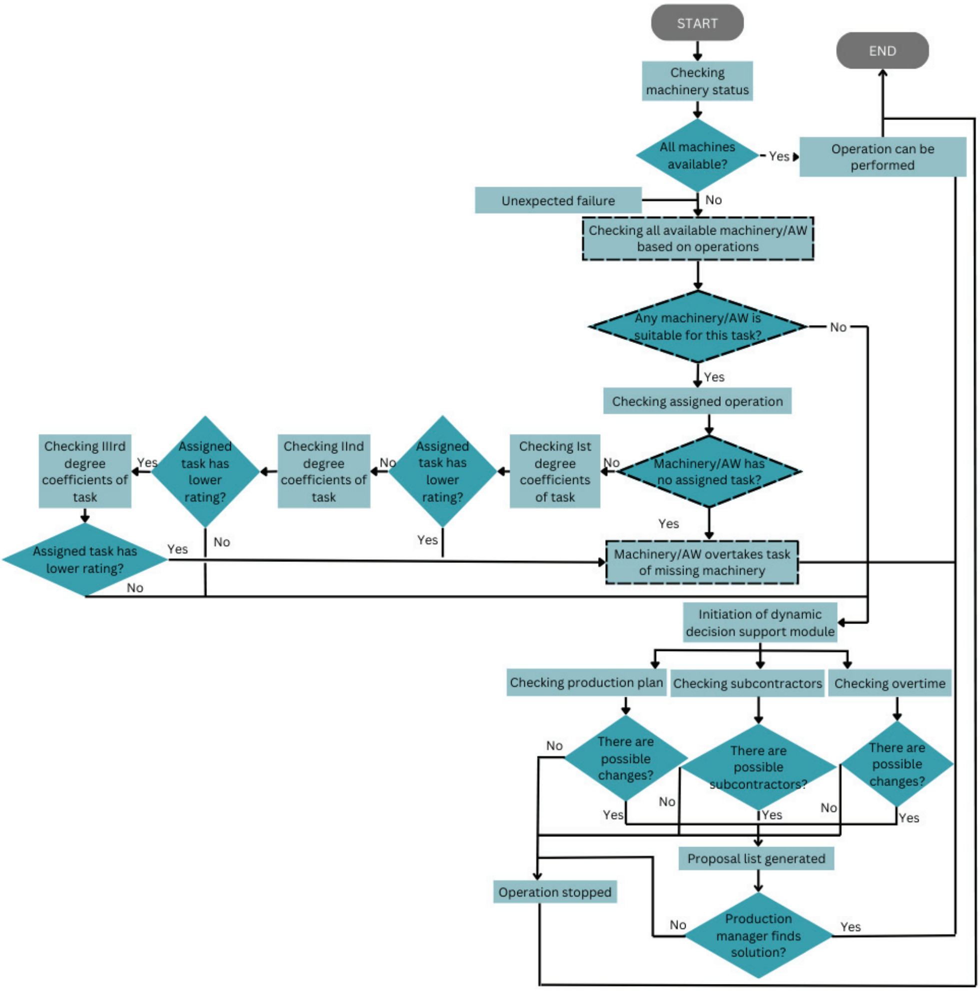


Fig. 18. DSM DPP algorithm for the machinery section when the company has an available automated machine

The most important part is that, when covering an employee or machinery by this cell, the time for changing its program should be evaluated. Thus, this is evaluated in the part of the optimization task.

3.6. Optimization Task

In accordance with the manufacturing process, the duration of each order can be estimated based on the specific operations required. Thus, the cumulative execution time of all orders can be computed if they are executed sequentially. The aim of this process is to optimize the scheduling of orders to ensure that all employees are engaged, and that all machines are utilized, thereby achieving the optimal utilization level, and reducing the overall execution time of orders by executing them concurrently.

The function for time minimizing is as follows:

$$\min T = \min_{1 \le i \le n} \left(\max_{1 \le i \le n} (tg_i) - \min_{1 \le i \le n} (tp_i) \right); \quad (31)$$

$$tp_i \le t_i \le tg_i; \quad (32)$$

$$tg_i \ge 0; \quad (33)$$

$$tp_i \ge 0; \quad (34)$$

$$t_i \ge 0; \quad (35)$$

$$i = \overline{1:n}, \quad (36)$$

where: T – process execution time;

t_{pi} – time of i production order initiation;

t_{gi} – time of i production order completion;

t_i – time of i production order processing;

i – production order number;

n – the total number of production orders.

The objective is to maximize the value generated by the worker or machine through benefits assessment. The created value should be the highest achievable value, and, to tackle this objective, a function for manual production is created:

$$\max P_{CF} = \max \left(\sum_{i=1}^{n} value_i - \sum_{i=1}^{n} \left(\sum_{j=1}^{m} tx_{ji} \cdot X_j + \sum_{k=1}^{r} ty_{ki} \cdot Y_k \right) \right); \quad (37)$$

$$value_i \ge 0; \quad (38)$$

$$tx_{ij} \ge 0; \quad (39)$$

$$X_j \ge 0; \quad (40)$$

$$ty_{ki} \ge 0; \quad (41)$$

$$Y_k \ge 0, \quad (42)$$

where: P_{CF} – production cash flow;

m – the total employee number;

r – the total machinery number;

$value_i$ – the value of production order i earned from this order (the amount which is left after eliminating the materials costs);

tx_{ji} – the working time of j employee in i production order;

X_j – the hourly costs of j employee;

ty_{ki} – the working time of k machinery in i production order;

Y_k – the hourly costs of k machinery;

j – employee number.

This optimization function might be extended based on the idea presented in Subsection 3.6 regarding the use of additional automated machines instead of machinery or employees. In case this option is available and has been selected, evaluation of the costs of reconfiguration must be included.

The optimization function of semi-automated production is as follows:

$$\max P_{CF} = \max\left(\sum_{i=1}^{n} value_i - \sum_{i=1}^{n}\left(\sum_{j=1}^{m} tx_{ji} \cdot X_j + \sum_{k=1}^{r} ty_{ki} \cdot Y_k\right) - \delta \sum_{i=1}^{w} tr_i \cdot Z_i\right); \quad (43)$$

$$tr_i \geq 0; \quad (44)$$

$$Z_i \geq 0, \quad (45)$$

where: w – the total number of replaced employees or machinery with automated machinery;

tr_i – the time for reconfiguration of i automated machinery;

Z_i – the hourly costs of i automated machinery reconfiguration;

$\delta = \begin{cases} 0, employee/machinery \rightarrow \ Automated\ machine{:}\ not\ initiated \\ 1,\ employee/machinery \rightarrow \ Automated\ machine{:}\ initiated \end{cases}$.

As this method reduces the time of production by lowering the consumed number of passive production hours, the company saves money by reducing energy consumption which is described in Subsection 4.6. Following this, the total value of saved money can be found by:

$$S_{ee} = \left(\sum_{k=1}^{r} (\mathrm{T}_k - \sum_{i=1}^{n} ty_{ki})e\right); \quad (46)$$

$$T_k \geq 0; \quad (47)$$

$$e \geq 0, \quad (48)$$

where: S_{ee} – the saved energy value in monetary expression after DSM DPP implementation;

T_k – the total planned production time of k machinery before DSM DPP;

e – the price of electricity per hour.

3.7. Section Summary and Insights

A mathematical model has been presented in this section. It is based on several data arrays:

- materials M;
- skills of employees C;
- the initial day plan P;
- task importance OW;
- task performance S.

The mathematical model follows the optimization task which:

- maximizes the profit of the company;
- minimizes the overall time for the production.

As an outcome, energy savings follow as the reduced time of the total production transforms to reduced stand-by hours when the machinery is wasting energy.

This section has presented an algorithm for a new product. Based on it, operational times and operations can be assigned to a new unproduced product so that it could be evaluated in algorithms. In addition, this section has presented a situation when a selection of automatic workplace for the replacement of employee or machinery can be done. Based on this, the optimization task was modified.

This model has been analyzed with real-life data from Company A and Company B. Experimental research with results shall be presented in Section 4.

4. TESTING OF THE DEVELOPED DSM DPP AT BUSINESS COMPANIES

4.1. Introduction

As the mathematical model and the DSM DPP method have already been described, tests and results shall be presented in this section. Observations and investigations were conducted in two companies – a metal processing company, and an automotive body repair company. Both of them belong to the SME category. This examination was made to show the versatility of this method – especially regarding the fact that one company manufactures products, while the other company offers services, and their sizes differ by almost 10 times, but the overall method was easily adapted to both of them and showed promising results in time saving and profit increasing. As the method is complex and requires several data arrays, multiple factors and values, it was checked only based on the employee absence algorithm. Materials, machinery, and the new product were only evaluated as '1' or '0' without any further investigation whether there is an available machine which could be used. Since the method works in the same manner for the presently mentioned groups of constituents, this was deemed sufficient for checking and testing to evaluate in this manner to save time and resources.

4.2. New Product Implementation

The developed method requires general information about the production, specifically, the operations, time and their sequence. However, a big range of products in SMEs are newly created offerings or niche products which do not have any historical precedent in terms of information; thus, technological grouping has been adapted in the method. As presented in the algorithm of the 'new product', there are two main sections, namely, the category and the level of complexity. The category can be selected by the type of the company as it can be the size of a product, the processed area, production operations, or any other feature. In metal processing the company category was grouped by the type of operations, such as welding, bending, turning, or cutting. Each of these categories involves three complexity levels. Based on products of a similar type, the new product should be assigned to one of the categories, and then to one of the complexity levels. Fig. 19 presents the described method, and this representation is derived from the data in the case study of Company A.

4.3. Data Arrays and Tests of Company A[4]

At first, the logic of the method has to be checked with only the core information to understand the logic.

There are 7 operations ongoing for the selected investigated product – a steel furniture leg (Fig. 20). These specific furniture legs are constructed from a steel

[4] The material in this section has previously been published in [132, 133]

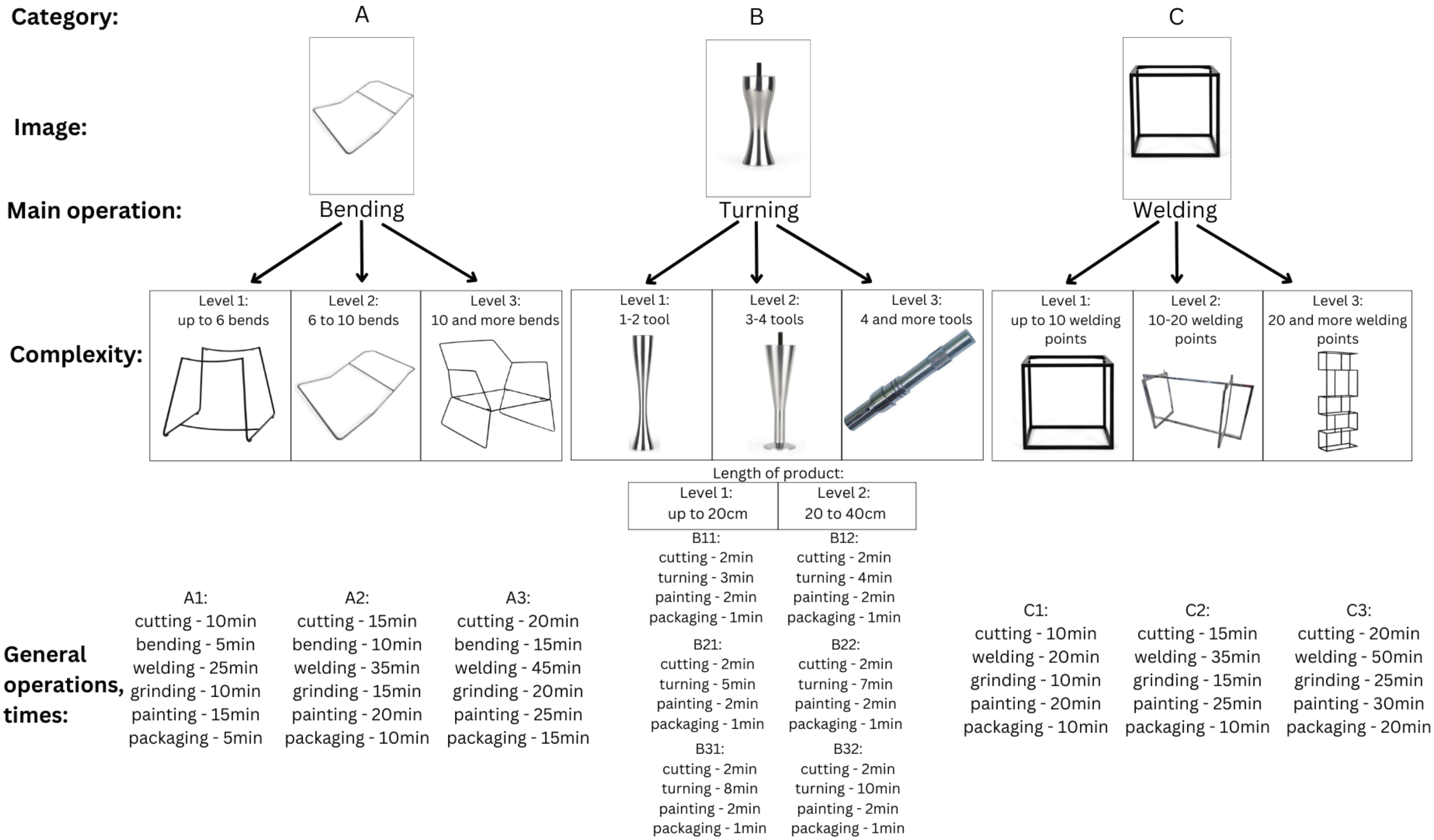


Fig. 19. Segmentation of products in Company A

tube, a perforated metal plate, a threaded stud, and a plastic cap. These furniture legs undergo such processes as cutting, punching, welding, and the finishing process, which includes either lacquering or painting.

Afterwards, they are carefully packaged in plastic bags. The packaging format, whether individually or in kits, is determined based on the clients' preferences. Company A mostly produces such products, and each employee has specific knowledge for each task.

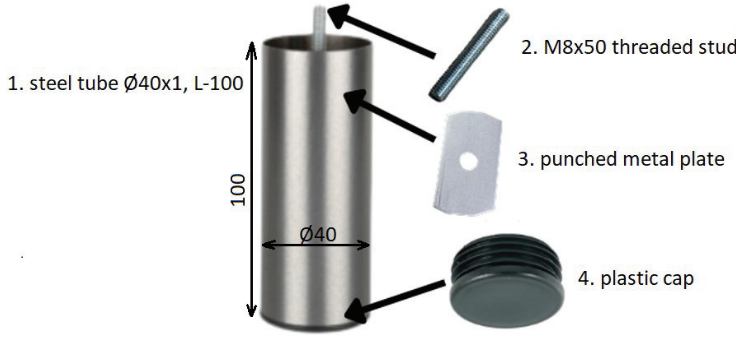


Fig. 20. Steel furniture leg. D40×L100 mm

The seven main technological operations to produce such a furniture leg are as following:

1 – the cutting operation;
1 – the punching operation;
3 – the 1st welding operation;
4 – the 2nd welding operation;
5 – the finishing operation;
6 – the assembling operation;
7 – the packaging operation.

Conducting a comprehensive evaluation of the machinery's operational status is of utmost importance. This investigation entailed in-depth analysis of production data aimed at assessing the effectiveness of individual machines designated for specific operations. Table 3 gives the number of machines available for each operation essential to the entire production process.

In this examination stage, the materials section is randomly selected as missing or not. This was agreed due to a lower loading on the system. Materials would normally follow the presented data array M, where different information is taken from the system automatically.

Table 3. Machinery assigned for each operation in Company A

Operation No.	The machine used for the operation	Quantity
1	Band saw machine	1
2	Disc saw machine	1
3	Automatic disc saw machine	1
4	Bending machine	1

Operation No.	The machine used for the operation	Quantity
5	Manual sander	2
6	Belt sander	1
7	CNC turning machine	1
8	Vertical milling machine	1
9	Hydraulic press	1
10	Welding machine	4
11	Powder coating booth (3x1.54x1.8m)	1
12	Powder coating booth (2x1.1x1.8m)	1
13	Hand saw	1

Based on the steps presented in the previous section, the first examinations were performed in the *Excel* program. This test is based on data from company and recreates situation in *Microsoft Excel*. This was made to check the logic of the method (Table 4).

Table 4. Data for employee replacement task

Machinery (Matrix E)	**Material (Matrix M)**	**Task (Matrix T)**	**Order (TN)**	**Operation (ON)**	**Employee (EN)**	**Is EN=1?**	**E*M*T Can employee work? (E*M*T)**	**Is task performed?**	**Result**
1	1	1	1	3	1	1	1	1	2
1	0	1	2	3	2	1	0	0	1
0	1	1	3	4	3	1	0	0	1
1	1	1	4	**4**	4	**0**	1	0	0
1	1	1	5	6	5	1	1	1	2
1	1	1	5	6	6	1	1	1	2
0	1	1	6	6	7	1	0	0	1
1	1	1	6	6	8	1	1	1	2
1	1	1	5	7	9	1	1	1	2
1	0	1	5	7	10	**0**	0	0	0
0	1	1	6	7	11	1	0	0	1
1	1	1	6	7	12	1	1	1	2
1	1	1	5	5	13	1	1	1	2
1	1	1	6	5	14	1	1	1	2
1	1	1	7	2	15	1	1	1	2
1	1	1	8	2	16	1	1	1	2
1	0	1	7	1	17	1	0	0	1
1	1	1	8	1	18	1	1	1	2

The columns labeled *Matrix E*, *Matrix M*, and *Matrix T* indicate the availability of equipment, materials, and the task itself accordingly. If any of these elements are missing, employees cannot perform their duties even if they are present at the workplace. In this process, these columns were populated with randomly selected values of ‘1’ or ‘0’. Each employee is assigned a specific task (operation), and an associated order number, which are recorded in the ‘TN’ and ‘ON’ columns. The identification numbers of the employees are provided in the ‘EN’ column. The ‘Is EN=1?’ column serves the purpose of verifying whether a particular employee is present at work or not. The outcomes in the ‘Result’ column can assume the following values:

- ‘1’ means that an employee is on stand-by and ready for any task since the working conditions are hindered by factors such as material shortages, equipment unavailability, or other similar reasons;
- ‘2’ denotes that everything is proceeding as planned, and that no changes are needed;
- ‘0’ has two interpretations: either there is no need for any action because neither an employee nor a task is present, or it signals the necessity to find a replacement for the task. The need for replacement arises when the values in the ‘E*M*T’ column equal to ‘1’.

The subsequent phase involves locating an individual possessing the necessary skills to fulfill the task. To facilitate this, a skills matrix is activated, as depicted in Table 5. Columns from O1 to O7 represent specific knowledge values for each operation. The examination in Company A was made by selecting 18 employees from one shift. Thus, all the information about the skills, salaries, or absence will be derived from the same group of people. Once an employee with the requisite skills has been identified, the evaluation process assesses whether the initially planned task is of a greater or lesser importance. This process unfolds in three stages, starting with an examination of the available employees who currently have no assigned tasks. Firstly, those are evaluated who are available and do not have an assigned task; thus it means that their result from the previous part is equal to ‘1’.

There are 5 such employees, but, for the exchange, only one is needed who could have more than 0.5 for O4. So, the selection starts from employees 2 and 3. To select between several options of the employees or machinery, it is necessary to check this with the optimization function – i.e., which option offers the highest profit value or the lowest time value. It could also be described by a new coefficient which would include an employee’s learning time, the quality factor of each operation, and the speed of operating the task. But, in general, in order not to complicate the method and data needed, of which, some could be biased because it depends on the evaluation from the production manager, it is agreed to select employee or machinery based on the optimization function. The hourly costs of employees are given in Table 6, whereas the hourly costs of machinery are given in Table 7. As in this case when the value is the same, it is selected randomly, but the system would follow the additional described parameters. Each employee in this examination has been assigned a number so that depersonalized data could be used.

Table 5. Matrix of skills to check employee replacement

Employee No.	Result	Operations						
		O1	**O2**	**O3**	**O4**	**O5**	**O6**	**O7**
1	2	0.5	0.5	0.75	0.75	0	1	1
2	1	0.5	0.5	0.75	**0.75**	0	1	1
3	1	0.5	0.5	0.75	**0.75**	1	0.75	1
4	0	0.25	0.5	0.75	0.75	0	0.75	1
5	2	0.25	0.25	0	0	0	1	1
6	2	0	0	0	0	0	1	1
7	1	0	0	0	0	0	1	1
8	2	0	0	0	0	0	1	1
9	2	0	0	0	0	0	1	1
10	0	0	0	0	0	0	0.75	1
11	1	0	0	0	0	0	0.75	1
12	2	0.5	0.5	0	0	0	1	1
13	2	0.5	0.5	0	0	1	1	1
14	2	0.5	0.5	0	0	1	0.75	1
15	2	1	0.75	0	0	0	0.75	0.75
16	2	1	1	0	0	0	1	0.75
17	1	1	1	0	0	0	1	0.75
18	2	1	1	0	0	0	1	1

Table 6. Hourly wage of employees in Company A

Employee No.	Hourly wage, Eur
1	9.25
2	9.5
3	9.5
4	9
5	4.7
6	4.5
7	4.5
8	4.75
9	4.5
10	4.75
11	4.75
12	4.75
13	7
14	7
15	6

Employee No.	Hourly wage, Eur
16	4.75
17	4.75
18	4.5

If only the employees who were in the group with Result = 2 (occupied with a task) could be selected, a three-step evaluation process would be initiated. In this case, only Employee No. 1 could perform the task of the absent employee, so it is necessary to evaluate which of them has a more valuable task at hand. Employee No. 1 was performing order 1, whereas the absent employee would be performing order No. 4. The coefficients of those tasks must be checked. A Ist degree check is presented in Table 8. As seen, the Ist degree coefficient of the absent employee was higher; thus, Employee No. 1 was bound to be switched to this new task.

Table 7. Machinery hourly costs in Company A

Operation No.	Hourly costs, Eur
1	5
2	3
3	3
4	3
5	1
6	5
7	10
8	2
9	1
10	7
11	20
12	15
13	0.5

Table 8. Check of task importance factors (Ist degree)

Order no.	Ist degree		IInd degree		IIIrd degree			
	f_1	f_2	f_3	f_4	f_5	Ist degree coeff.	IInd degree coeff.	IIIrd degree coeff.
1	0.1	0.11	0.05	0.08	0.82	0.21	0.13	0.82
2	0.12	0.13	0.21	0.21	0.09	0.25	0.42	0.09
3	0.81	0.05	0.55	0.37	0	0.86	0.92	0
4	0.15	0.12	0.15	0.07	0	0.27	0.22	0
5	0.75	0.65	0.24	0.89	0	1.4	1.13	0
6	0.88	0.5	0.18	0.89	0,00	1.38	1.07	0
7	0.79	0.47	0.49	0.41	0.75	1.26	0.9	0.75
8	0.2	0.39	0.58	0.25	0	0.59	0.83	0

If only this were otherwise, the IInd degree coefficient would be initiated. Table 9 presents values when a IInd degree coefficient must be checked. In this case, the IInd degree coefficient is lower for Employee No. 1 (0.13 compared to 0.22); so, the IIIrd degree coefficient is evaluated, and since it is higher for Employee No. 1 (0.82 compared to 0), the decision support module is activated since this employee is not able to perform the task of Employee No. 4.

Table 9. Check of task importance factors (IInd degree)

Order No.	Ist degree		IInd degree		IIIrd degree			
	f_1	f_2	f_3	f_4	f_5	Ist degree coeff.	IInd degree coeff.	IIIrd degree coeff.
1	0.1	0.2	0.05	0.08	0.82	0.3	0.13	0.82
2	0.12	0.13	0.21	0.21	0.09	0.25	0.42	0.09
3	0.81	0.05	0.55	0.37	0	0.86	0.92	0
4	0.15	0.12	0.15	0.07	0	0.27	0.22	0
5	0.75	0.65	0.24	0.89	0	1.4	1.13	0
6	0.88	0.5	0.18	0.89	0,00	1.38	1.07	0
7	0.79	0.47	0.49	0.41	0.75	1.26	0.9	0.75
8	0.2	0.39	0.58	0.25	0	0.59	0.83	0

At the end of this test, it was agreed that the logical steps should follow the required results, and replanning is possible with such a sequence of steps. Thus, further examinations were made with *Matlab*. In order to start the program, additional information is required because the presented check does not simulate several production orders at once. Table 10 presents the different information required for this method. This information is well known for each company, and it does not require any specific knowledge or complex data collection.

Evaluation in this subsection is performed with the information from Company A. In Table 11, a fragment of 9 production orders can be seen. In total, data of 16 production orders was taken from Company A to evaluate and generate the production orders and working plans. This information will be used to replan the production and respond to dynamic processes. The data of operations and time spent for each operation is shown in Table 11. Each product might have a unique sequence of operations and a different time for operations.

The data from Company A required to run DSM DPP is given in Table 12.

As described, the company has to set specific factors to have the proper three-stage evaluation when it is needed. For that, Table 13 presents numbers for this specific case study.

Table 10. Descriptions of the required information for DSM DPP

Column	Short description
Client	Clients' name (in this research, based on privacy rules, names are marked as a, b, c, etc.)
Order No.	It is unique coding for orders; in one order, several different products could be ordered
Product No.	Each product has it is own coding
Quantity	The number of pieces per order
Order span, days	Time in days from the order confirmation to the delivery date
Order date	The date when the order was confirmed
Value, Eur	Total value received from the client of the specific product and quantity of the order in euros
Value of production, Eur	The amount of money left after the raw materials value has been taken away in euros
Delivery type	Clients can agree to get a partial delivery – i.e., to divide the order in several pieces. In this column, a percentage of the minimum required order quantity is given.
Payment type	Clients might pay in advance (value '-1') or have postponed payment (30, 60 days)
Operations	Operations must be done in the correct order, and this column represents which operation is needed, and when each operation could be done
Time of operation for 1 piece, minutes	Minutes for each operation for one piece of product
Client rating	Each client is ranked based on several individual aspects – the percentage of its order compared with the total orders in the company, the payment in time ratio, specific agreements, etc.
Delay ratio	The percentage of delivered late orders out of all previous orders
New product	If the product is new, the value is '1'. If such a product has already been produced previously, the value is '0'
Shipping	The order might be delivered at place (DAP), or the client should organize transport or pay for it when it is *Ex Works* (EXW) conditions. *DAP* means that all the specified order span is with the shipping included (which can take up to several days)
Complexity of product	Scale to 1 – the bigger is the value, the more complex is the product, and the time spent for the production is longer
Rejection ratio	The percentage of how many products were rejected in previous production orders
Subcontractors	If the product needs operations made by other companies, the value is '1'. If the product is made only in this company, the value is '0'
Time in subcontractors, days	If a subcontractor is needed, the time required for it is provided
Materials	Each product has a specification of whatever raw materials are needed, and list of specifications is required. Here, to simplify data, materials are coded

Table 11. Operational times of the investigated production orders in Company A (fragment)

Client	Operations	Time of operation for 1 piece, minutes										
		1,2	3	4	5	6	7	8	9	10	11,12	13
a	10,5,11,13				30					120	60	12
a	1,2,4,10,5,11,13	45		30	25					130	45	9
a	1,2,7,10,5,11,12,13	10			20		15			35	40	9
a	1,2,4,10,5,11,12,13	30		20	20					75	25	15
a	1,2,4,10,5,11,13	30		20	20					75	35	15
a	5,11,13				30						30	15
a	1,2,10,5,11,13	15			30					60	40	18
b	3,9,10,6,11,12,13		360			480			72	480	920	216
c	1,2,9,10,6,11,12,13	100				120			20	200	60	60
c	3,10,6,11,12,13		200			360				300	420	240
d	1,2,8,10,6,11,12,13	150				75		300		140	50	90
e	4,11,13			30							5	6
...												

Table 13. Task importance factors in Company A

Factor	Value	Degree
Delivery date (f_1)	0.8	1
The need of this task for further processes (f_2)	0.9	1
Quantity (f_3)	0.75	2
Clients ranking (f_4)	0.7	2
Extra requirement (f_5)	0.2	3

For this test model, the manual data upload is selected because the idea is that the information about equipment, materials and employees would be uploaded in the system in quasi-real-time.

After the method has been checked by using different methods, the program with *Matlab* is created. It needs several data arrays, which follow Section 3.

Table 12. Data from Company A required for DSM DPP

Client	Order No.	Product No.	Quantity	Order span, days	Value, Eur	Value of production, Eur	Delivery type	Payment type	Client rating	Delay ratio	New product	Shipping	Complexity of product	Rejection ratio	Subcontractors	Time in subcontractors, days	Materials
a	1	P1	1	28	186	86	0	30	0.8	50	1	1	0.5	0	0	0	1. 2
a	2	P12	1	21	231	197	0	30	0.8	50	0	1	0.7	10	0	0	1. 2
a	2	P2	1	21	145	74	0	30	0.8	50	0	1	0.7	10	0	0	2. 3. 4
a	2	P3	1	21	296	141	0	30	0.8	50	0	1	0.5	0	0	0	2. 3
a	2	P4	1	21	304	156	0	30	0.8	50	0	1	0.3	0	0	0	2. 3
a	2	P5	1	21	171	65	0	30	0.8	50	0	1	0.2	0	1	4	1
a	2	P6	1	21	245	100	0	30	0.8	50	0	1	0.4	0	0	0	2
b	3	P7	720	35	4320	2265	0	30	0.7	80	0	1	0.3	10	0	0	2. 3
c	4	P7	100	21	700	365	50	30	0.7	65	0	1	0.3	10	0	0	2. 3
c	4	P8	200	21	1280	780	0	30	0.7	65	0	1	0.2	10	0	0	2
d	5	P9	300	10	438	151	0	30	0.9	25	0	1	0.4	10	0	0	2
e	6	P10	10	10	21	11	0	-1	0.6	50	1	1	0.2	0	0	0	4
e	6	P11	10	10	18	8	0	-1	0.6	50	1	1	0.2	0	0	0	5
a	7	P13	30	20	289	220	0	30	0.8	50	0	1	0.3	5	0	0	2. 6
a	7	P14	20	20	197	130	0	30	0.8	50	0	1	0.3	8	0	0	2. 6
b	8	P7	720	40	4320	2265	0	60	0.7	80	0	1	0.3	5	0	0	2. 3
f	9	P15	432	20	514	287	0	30	0.75	20	0	1	0.5	10	0	0	1. 2
...																	

The matrix of skills in this situation, when 18 employees and 13 different possible operations are involved, would look like this:

$$C = \begin{pmatrix}
1 & 0{,}75 & 0{,}75 & 0{,}5 & 0 & 0 & 0 & 0 & 0 & 0{,}5 & 0{,}75 & 0 & 1 & 1 \\
2 & 0{,}75 & 0{,}75 & 0{,}5 & 1 & 0 & 0 & 0 & 0 & 0{,}5 & 0{,}75 & 0 & 1 & 1 \\
3 & 0{,}75 & 0{,}75 & 0{,}5 & 0 & 0 & 0 & 0 & 0 & 0{,}5 & 0{,}75 & 1 & 0{,}75 & 1 \\
4 & 0{,}5 & 0{,}5 & 0{,}25 & 0 & 0 & 0 & 0 & 0 & 0{,}5 & 0{,}75 & 0 & 0{,}75 & 1 \\
5 & 0{,}5 & 0{,}5 & 0{,}25 & 0 & 0 & 0 & 0 & 0 & 0{,}25 & 0 & 0 & 1 & 1 \\
6 & 0{,}25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
7 & 0 & 0 & 0 & 0{,}75 & 0{,}25 & 0 & 0 & 0{,}75 & 0 & 0 & 0 & 1 & 1 \\
8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
9 & 0 & 0{,}25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
10 & 0 & 0 & 0 & 0 & 1 & 0{,}75 & 0 & 0{,}5 & 0 & 0 & 0 & 0{,}75 & 1 \\
11 & 0 & 0{,}25 & 0 & 0 & 0{,}75 & 0{,}5 & 0 & 0{,}5 & 0 & 0 & 0 & 0{,}75 & 1 \\
12 & 0{,}75 & 0{,}75 & 0{,}5 & 0 & 0 & 0 & 0 & 0 & 0{,}5 & 0 & 0 & 1 & 1 \\
13 & 0{,}75 & 0{,}75 & 0{,}5 & 0 & 0 & 0 & 0 & 0 & 0{,}5 & 0 & 1 & 1 & 1 \\
14 & 0{,}5 & 0{,}5 & 0{,}5 & 0 & 0{,}75 & 0{,}5 & 0 & 0 & 0{,}5 & 0 & 1 & 0{,}75 & 1 \\
15 & 1 & 1 & 1 & 0 & 0{,}25 & 0 & 1 & 0{,}75 & 0{,}75 & 0 & 0 & 0{,}75 & 0{,}75 \\
16 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0{,}75 \\
17 & 1 & 1 & 1 & 0 & 0{,}75 & 0{,}75 & 0 & 0{,}5 & 1 & 0 & 0 & 1 & 0{,}75 \\
18 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1
\end{pmatrix}. \quad (49)$$

The second column of matrix C is left blank since this is the result of S matrix columns, and this was generated automatically for these testings.

In this study, the duration of one working day's shift was divided by half an hour, considering the shortest possible order duration. To facilitate this, an order matrix was constructed, where the data is segmented into half-hour intervals. Each 30-minute slot can be allocated to different operations, and the sequence of operations can be modified every half an hour. Fig. 21 illustrates an example of a shift-spanning work schedule. Different operations are color-coded in Fig. 21. This shift is assigned to work on multiple orders, but it is apparent from the chart that several orders are not currently in progress.

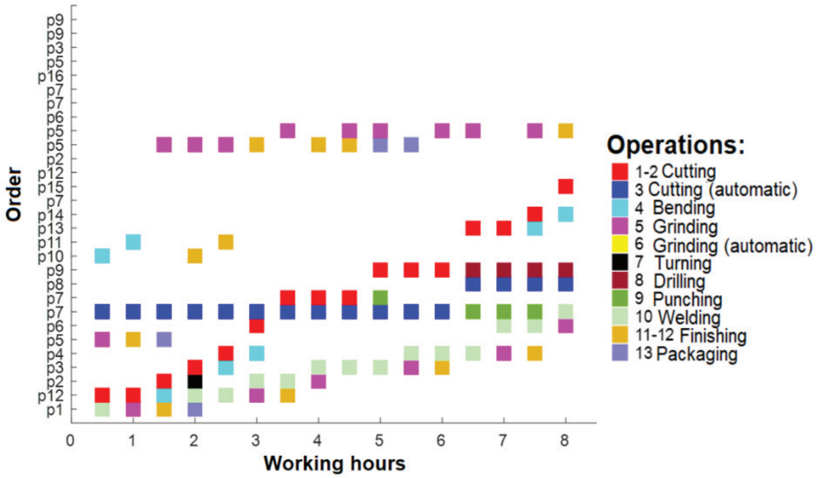


Fig. 21. Generated production plan for 1st shift in Company A

Furthermore, a matrix documenting the tasks completed by each active employee is generated. This matrix illustrates the specific tasks assigned to each employee and identifies the employees without assigned tasks, represented as blank spaces in Fig. 22.

Fig. 22. Generated employees work plan for 1st shift in Company A

This study delves into a real-life scenario, by analyzing a production plan comprising the previously mentioned 16 production orders. A total of 18 employees operate during a single shift, who are capable of performing 13 different operations. The initial evaluation occurs without optimization. If production orders are processed in the order of their input dates, after 16 working hours, the work schedule resembles the depiction in Fig. 23, and the task allocations for employees are reflected in Fig. 24.

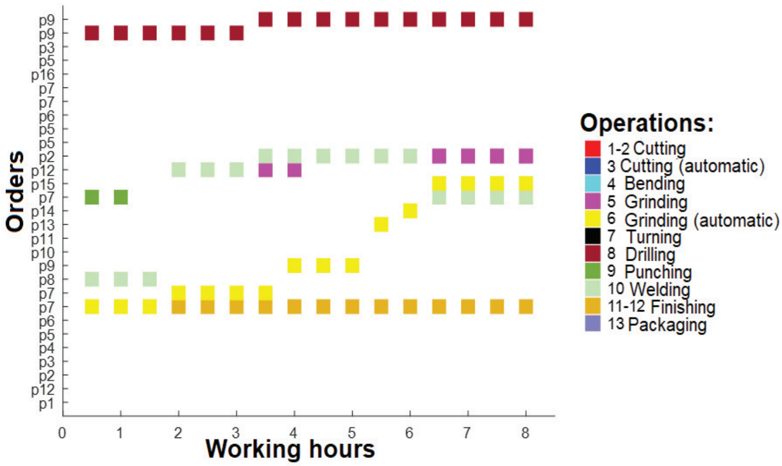


Fig. 23. Generated production plan for 2nd shift in Company A

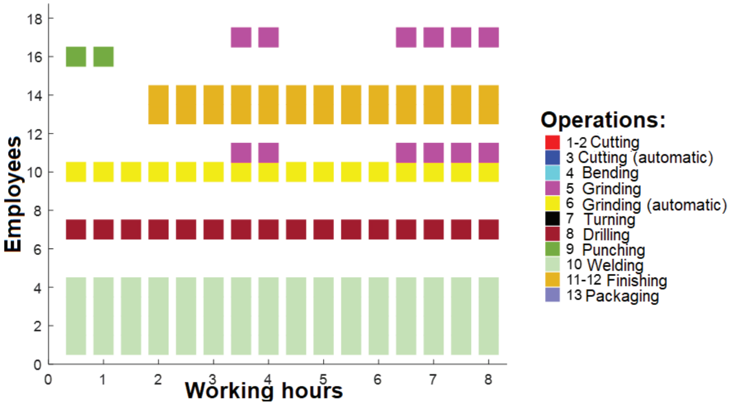


Fig. 24. Generated employees work plan for 2nd shift in Company A

As depicted in Fig. 23, it is evident that only a limited number of orders are performed during the second 8-hour timeline, which indicates underutilization of both the machinery and the employees, as visualized in Fig. 24. Consequently, there is a pressing need for optimization to enhance the overall performance.

The current investigation revolves around the calculation of the duration required for each order, while taking into account their respective operations. Subsequently, the average order duration is computed, and orders exceeding this average are identified. These orders are then subdivided into smaller units to ensure that their duration does not surpass the computed average, thereby ensuring a more equitable distribution of operations among employees. This strategy results in an increase in the total number of orders, by reaching a total of 29, as larger orders are broken down into smaller components.

The outcomes presented in Fig. 25 reveal that although there has been an improvement in the number of active orders after the initial 16 hours, the results still fall short of optimization. The implementation of optimization measures has led to a higher workload allocation for employees, as illustrated in Fig. 26.

An additional round of optimization was carried out, focusing on prioritizing production orders by considering several crucial factors. Specifically, the order quantity, the payment type, the client rating, and the order duration were identified as the most influential factors affecting the overall profitability. These criteria were employed to rank and schedule production orders with the aim of maximizing profitability. Based on the most recent findings following this optimization effort, it is apparent that the number of active production orders has remained relatively consistent, as shown in Fig. 27. However, there has been a significant increase in the variety of tasks undertaken by employees, which leads to a higher demand on the machinery resources, as depicted in Fig. 28. Since the operations are assigned to employees based on their level of skills, the employees perform tasks which they are capable of doing best. Based on I5.0 priorities for resilient manufacturing, the capacity to withstand or to recover quickly from difficulties is increased when employees can perform a wider range of tasks and improve their skills over time instead of performing only one operation every single time. Nevertheless, it is important to note that employees are not operating at their full capacity, which suggests that there may be room for further optimization in aligning the workforce with the available machinery resources.

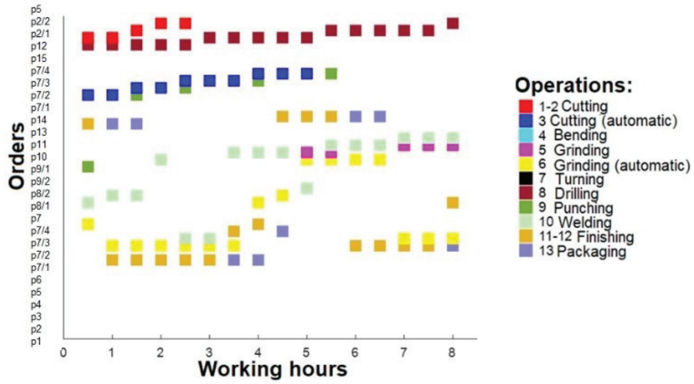


Fig. 25. Generated production plan for 3rd shift in Company A after 1st optimization

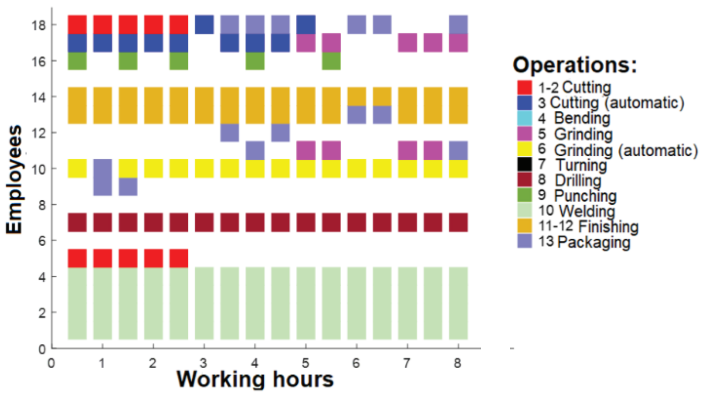


Fig. 26. Generated employees work plan for 3rd shift in Company A after 1st optimization

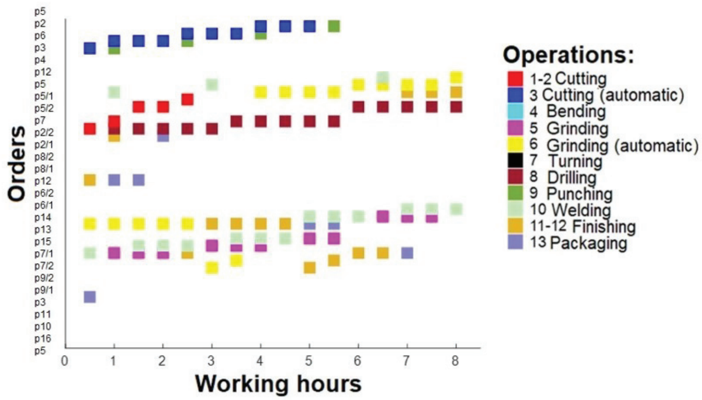


Fig. 27. Generated production plan for 3rd shift in Company A after 2nd optimization

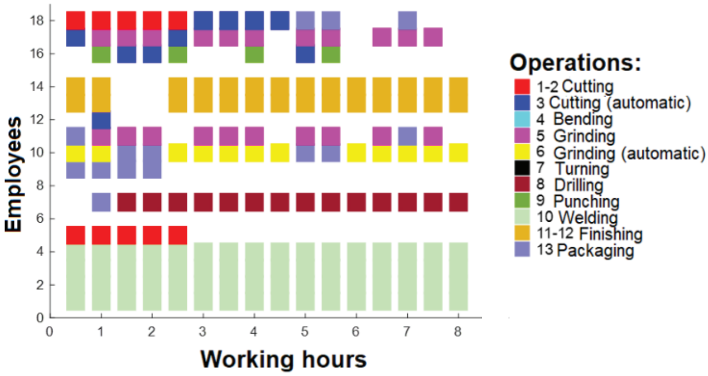


Fig. 28. Generated employees work plan for 3rd shift in Company A after 2nd optimization

After conducting analysis which identified specific employees as exceeding operational requirements, a third round of optimization was commenced. Specifically, three employees, namely, employees 6, 8, and 9, were terminated due to their limited capacity to carry out high-quality tasks. Subsequently, a revised work plan was devised, by outlining work schedules for all shifts (0–8 hours, 8–16 hours, and after 16 hours).The work plan for the first shift is illustrated in Figs. 29 and 30, while the second shift is depicted in Figs. 31 and 32. The final shift, which was previously examined in this section, is presented in Figs. 33 and 34. The total number of divided orders has now reached 44.

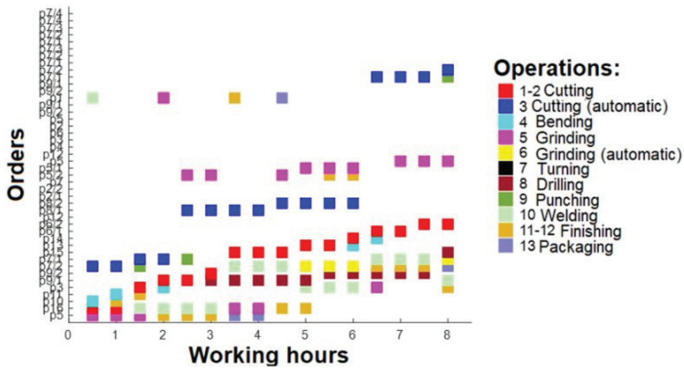


Fig. 29. Generated production plan for 1st shift in Company A after 3rd optimization

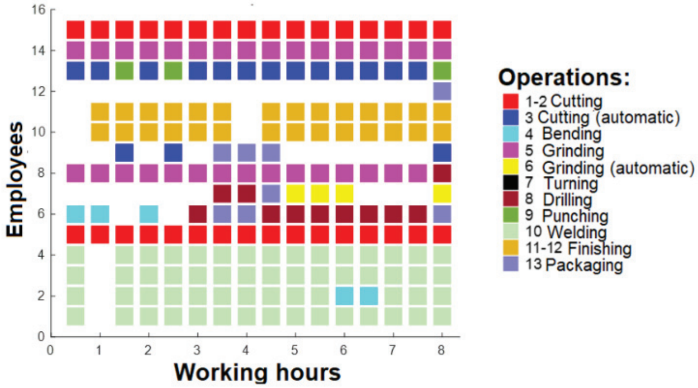


Fig. 30. Generated employees work plan for 1st shift in Company A after 3rd optimization

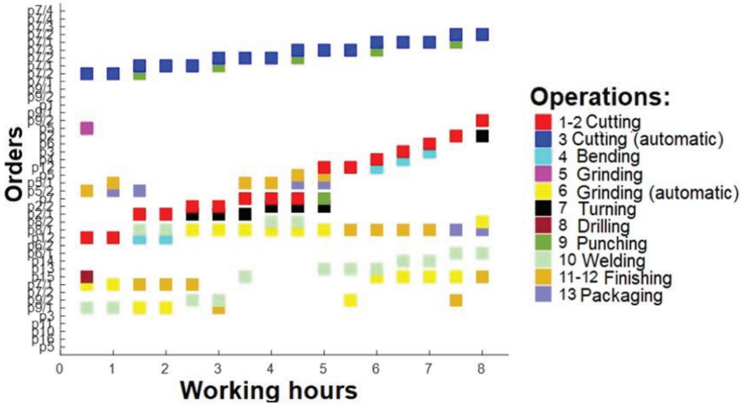


Fig. 31. Generated production plan for 2nd shift in Company A after 3rd optimization

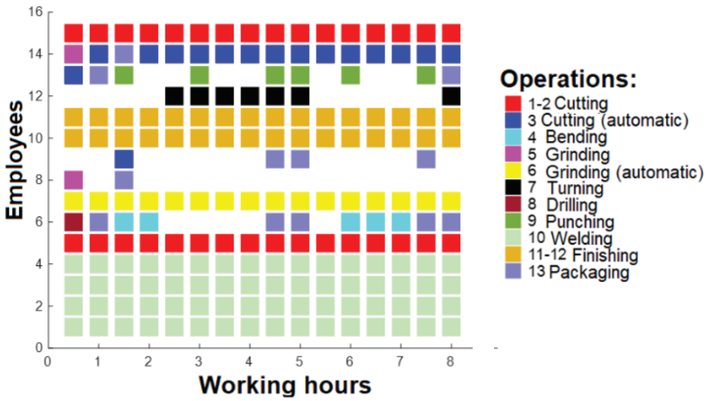


Fig. 32. Generated employees work plan for 2nd shift in Company A after 3rd optimization

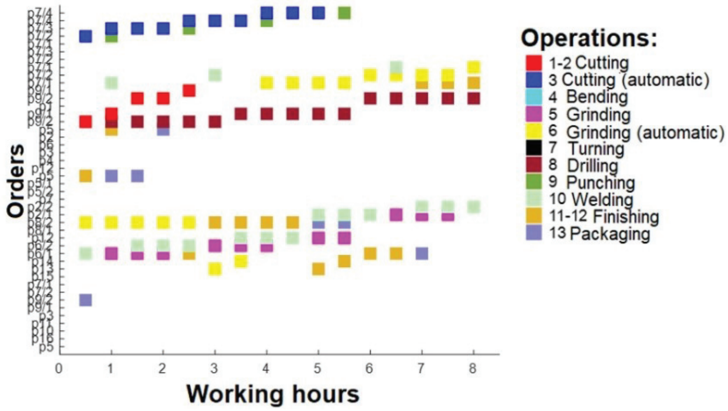


Fig. 33. Generated production plan for 3rd shift in Company A after 3rd optimization

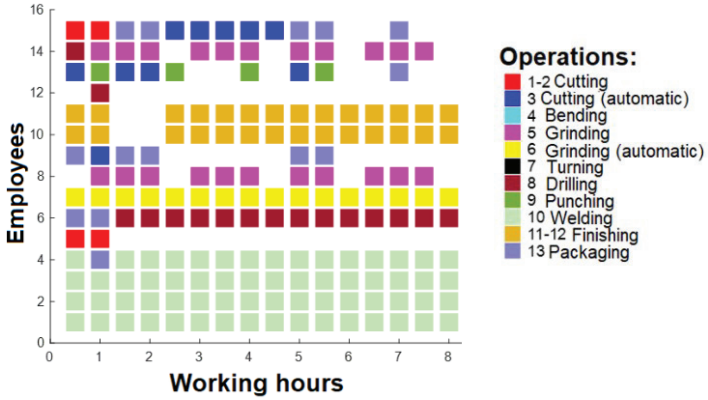


Fig. 34. Generated employees work plan for 3rd shift in Company A after 3rd optimization

After implementing the optimization measures as described, there has been a reduction in the overall production time for all orders. To be precise, the cumulative production time for these 29 orders has been reduced from 47 hours to 42 hours. The production scenarios before and after the third round of optimization can be visually compared , with the initial total time of 47 hours, and the subsequent 10% time savings, as illustrated in Figs. 35 and 36, respectively.

Upon completing a comprehensive three-stage optimization process utilizing the established methodology, it is clear that the existing production situation necessitates adjustments. This methodology not only offers immediate solutions for adapting production, but also serves as a valuable guide for the ongoing reorganization of production processes to achieve sustained improvements.

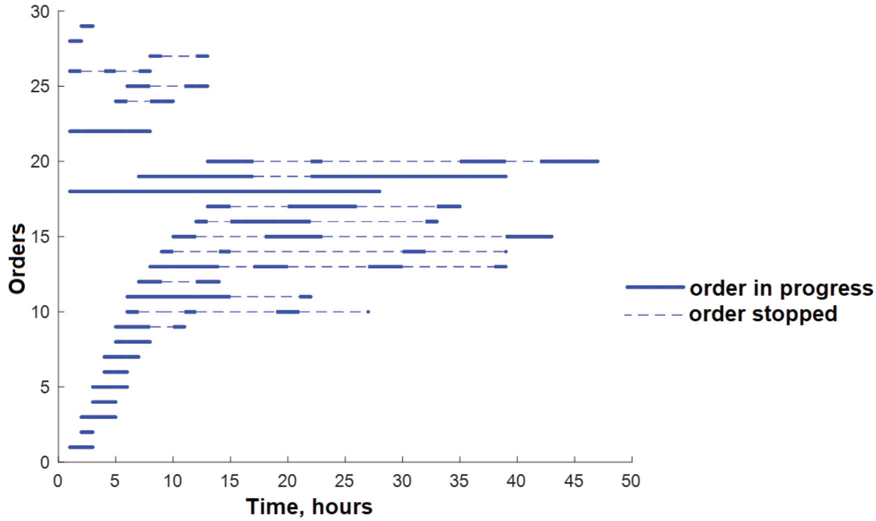


Fig. 35. Original production timelapse of 29 production orders in Company A

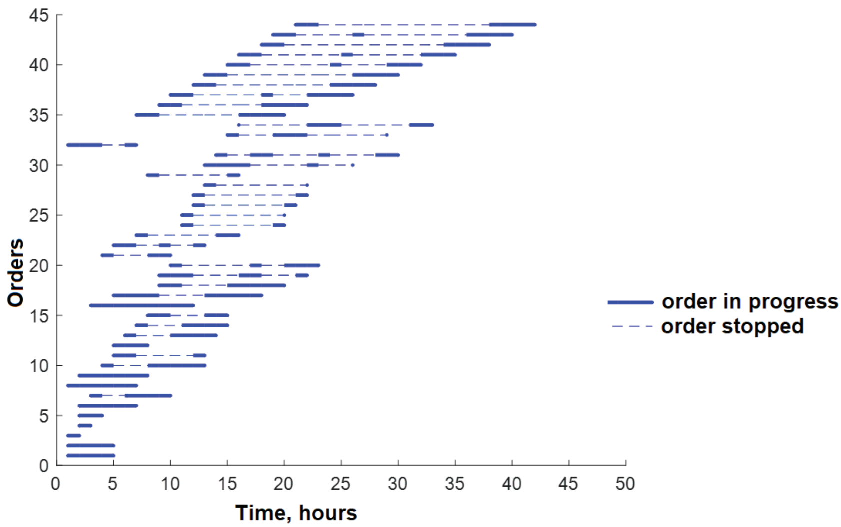


Fig. 36. Production timelapse of 44 production orders in Company A after DSM DPP

The experimental outcomes from DSM DPP testing underscore the necessity of introducing additional machinery to enhance the production scenario. Notably, the cutting operation, being an essential component for most orders, serves as a pivotal bottleneck within the production process. Consequently, any improvements in this operation would yield significant advantages. Given its role as a prerequisite for subsequent tasks, any delays in the cutting process directly impact the flow of orders. Furthermore, the finishing operation, which is essential for the majority of orders, typically consumes two to three times more time than other operations. Thus, optimizing this step is another crucial measure for enhancing the order flow. Moreover, considering the exploration of potential subcontractors as a viable solution could provide an expeditious resolution to the current situation.

Additionally, it is advisable to contemplate investing in employee training, especially for those with more limited skill sets. Furnishing additional training opportunities to employees can expand their skill sets, by equipping them to handle a wider array of tasks. Neglecting this training may lead to operational inefficiencies, as demonstrated by the removal of three employees, which had a relatively minimal impact on the overall workflow.

These concise remarks mark the beginning of investigation into the effectiveness of DSM DPP. It is crucial to acknowledge that conducting more extensive experiments would provide a more precise and reliable assessment of the method's effectiveness.

3-month monitoring was conducted to find out how much time could be saved at Company A. During this test, 491 production orders were run through the system. Preliminary findings indicate that the implementation of the DSM DPP method enables notable time savings in the manufacturing processes of the selected Lithuanian company. These time savings, achieved through optimized process reorganization, offer the potential for corresponding energy savings. The observed three-month period (from November 2022 to February 2023) demonstrates promising outcomes, which suggests that the given approach has the potential to improve the energy efficiency in manufacturing operations. As mentioned above, the total period of examination was 72 working days. After DSM DPP adaptation, all of these orders were accomplished in 68 days, thus giving an average of 5% time savings. This is shown in Fig. 37.

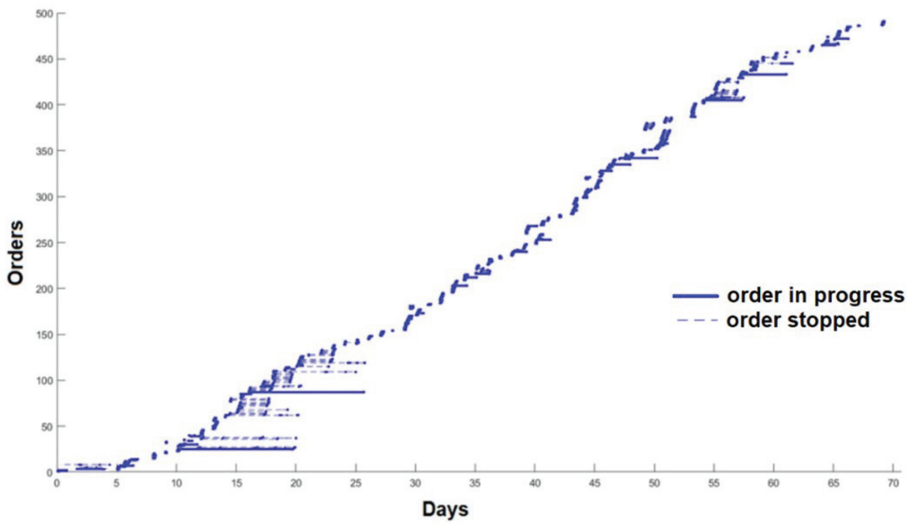


Fig. 37. Production timelapse of 491 production orders in Company A after DSM DPP

4.4. Data Arrays and Tests of Company B

In order to outline the universality of the method, another company was investigated, specifically, an automotive body repair company. This study was comprised of two distinct observations. The first observation involved evaluating the past performance over a three-month period so that to assess the efficacy of the DSM DPP method. The second observation involved providing the company with a production plan to evaluate the adaptability of the method and confirm or refute its effectiveness.

Each employee in this company has specific skills for 9 tasks mentioned in Subsection 2.4.2, and thus matrix C is created for Company B:

$$C = \begin{pmatrix} 1 & 1 & 0{,}75 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 1 & 0 & 0 & 0{,}75 & 1 & 0{,}25 & 1 & 1 & 1 \\ 3 & 1 & 0{,}5 & 0{,}75 & 1 & 1 & 1 & 1 & 1 & 1 \\ 4 & 1 & 0 & 0 & 0{,}25 & 1 & 0 & 1 & 0{,}25 & 1 \\ 5 & 0{,}5 & 0 & 0 & 0{,}25 & 1 & 0 & 0{,}5 & 1 & 1 \\ 6 & 0{,}5 & 0 & 0 & 0{,}25 & 1 & 0 & 0{,}5 & 1 & 1 \end{pmatrix}. \quad (50)$$

Regarding the initial observation, a total of 24 production orders were executed between December 12, 2022, and March 24, 2023, over a period of 72 working days. After implementing the DSM DPP method, the analysis indicated that the same number of orders could have been completed within 68 working days, thus reflecting a reduction in the production time of approximately 5%. The timeline of orders after the adaptation of methods is shown in Fig. 38.

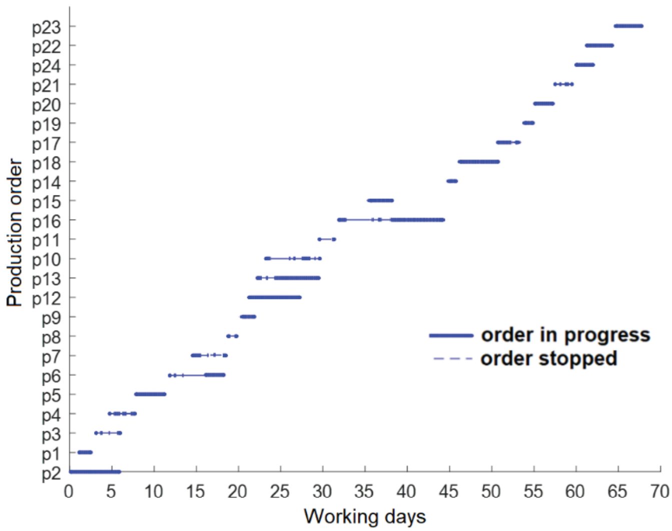


Fig. 38. Production timelapse of 24 production orders in Company B after DSM DPP

Another observation was made with the working plan of 3 days. The initial data is given in Table 14. This is the main information about the orders which is required for this method. Table 14 presents information from the company; according to their schedule, these 5 orders are expected to be completed in 3 working days.

Table 14. Initial production plan for 3 days in Company B, 1st test

Client	Order no.	Sum of order, Eur	Money for work, Eur	Operations	Operation time, minutes									Ratio of company	Complexity of order	Rejection ratio	Materials
					1	2	3	4	5	6	7	8	9				
a	1	1000	650	1, 4, 5, 6, 7, 9	120			180	60	180	120		60	0.7	0.2	0.1	1, 2
a	2	800	550	1, 4, 5, 6, 7, 9	120			120	60	120	120		60	0.7	0.2	0.1	1, 2
b	3	150	120	5, 8, 9					60			420	30	0.5	0.2	0.1	1
b	4	400	300	1, 3, 4, 5, 6, 7, 8	30		120	240	60	60	120	120		0.5	0.2	0.1	1, 2, 3
c	5	1500	1200	1, 4, 5, 6, 7, 8	30			840	60	240	30	240		0.9	0.9	0.1	1, 2, 3

DSM DPP was adapted to get planning results for this specific period. According to the program, all of these orders would fit in 18 hours, which is 25% faster than originally planned. The timeline of the production orders is presented in Fig. 39.

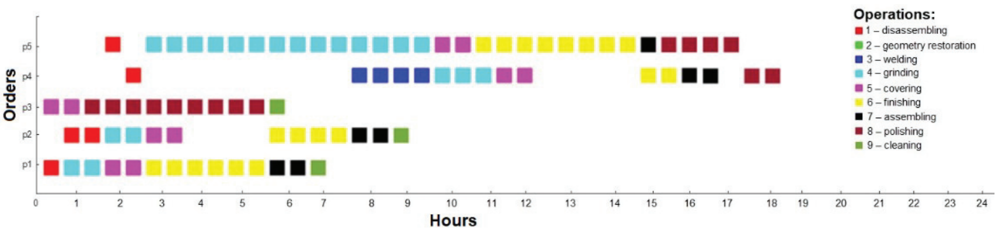


Fig. 39. Generated production plan for 3 days in Company B after DSM DPP, 1st test

The program gives results of the working plan of each specific employee. This is presented in Fig. 40. As shown, on the second working day, only a half of the employees were working fully and would not have been able to perform any other order. Having this information, it is visible what kind of orders could be taken to fill the unused hours.

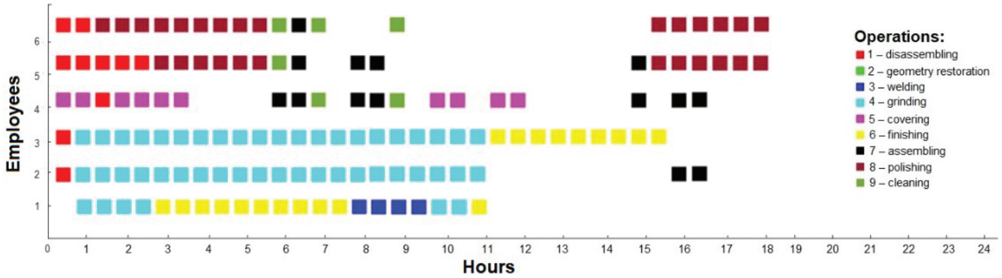


Fig. 40. Generated working plan for employees for 3 days in Company B after DSM DPP, 1st test

Based on this information, the company undertook to validate and check this sequence of orders for these specific 3 working days. The results showed that the use of this data led to the creation of a production plan which was a successful proposal. In total, the company spent 20 working hours and had the knowledge what could be planned additionally.

Another identical type observation was made with the working plan of 3 days. The initial data is given in Table 15. According to the company, these orders are scheduled for 3 working days.

Table 15. Initial production plan for 3 days in Company B, 2nd test

Client	Order No.	Sum of order, Eur	Money for work, Eur	Operations	Operation time, minutes									Ratio of company	Complexity of order	Rejection ratio	Materials
					1	2	3	4	5	6	7	8	9				
b	1	1300	725	1, 3, 4, 5, 6, 7, 8, 9	90		120	300	100	60	90	150	45	0.5	0.3	0.1	1, 2, 3
b	2	650	300	3, 4, 7			120	120			120			0.5	0.2	0.1	1, 2, 3
b	3	250	175	6, 8						100		60		0.5	0.1	0.05	1
b	4	320	265	1, 4, 6, 7	60			120		120	60			0.5	0.2	0.05	1, 2
c	5	2000	1500	1, 4, 5, 6, 7, 8, 9	160			720	120	240	100	120	120	0.9	0.5	0.05	1, 2
a	6	175	120	4, 5, 6, 8				60	120	120		150		0.7	0.2	0.1	1, 2
a	7	200	130	8, 9								360	60	0.7	0.2	0.1	1

DSM DPP was adapted to get the planning results for this specific period. The results showed that all of these orders would fit in 18 hours – which is 25% faster than originally planned. The timeline of production orders is presented in Fig. 41 – the direction from left to right corresponds to the first to third working days, as planned.

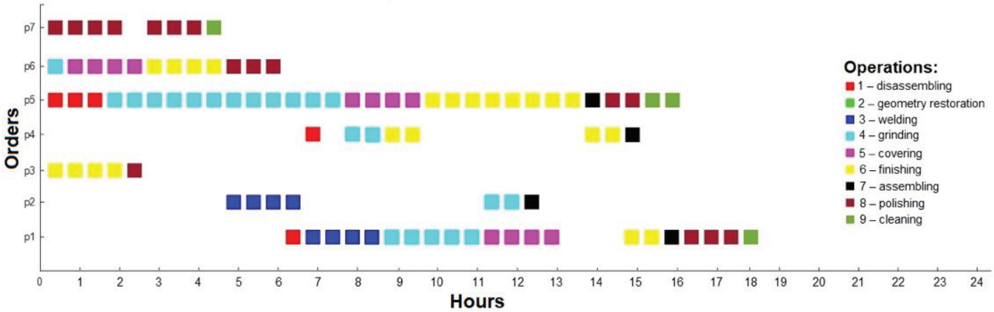


Fig. 41. Generated production plan for 3 days in Company B after DSM DPP, 2nd test

The program yields results of each employee's working plan. This is presented in Fig. 42.

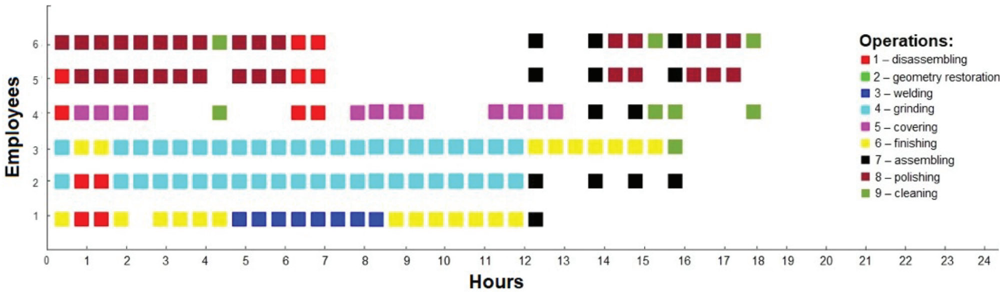


Fig. 42. Generated working plan for employees for 3 days in Company B after DSM DPP, 2nd test

Based on this information, the company accepted to validate and check this sequence of orders for these specific 3 working days. The results showed that the use of this scheduling led to created production plan which was a successful proposal. In total, the company spent 21 working hours and had the knowledge what could be planned in addition.

4.5. Compared Results from Company A and Company B

The obtained results confirmed that DSM DPP could be successfully used for different types of enterprises. The time savings and process efficiency were increased in both case study companies. In the examined companies, the implementation of the method for short term planning resulted in a higher time saving level compared to long term replanning. Short term examinations were performed once in Company A with 10% time savings and twice in Company B, which resulted in an average of 13% time savings. However, long term planning resulted in 5% time savings for both companies. The combined results are given in Fig. 43.

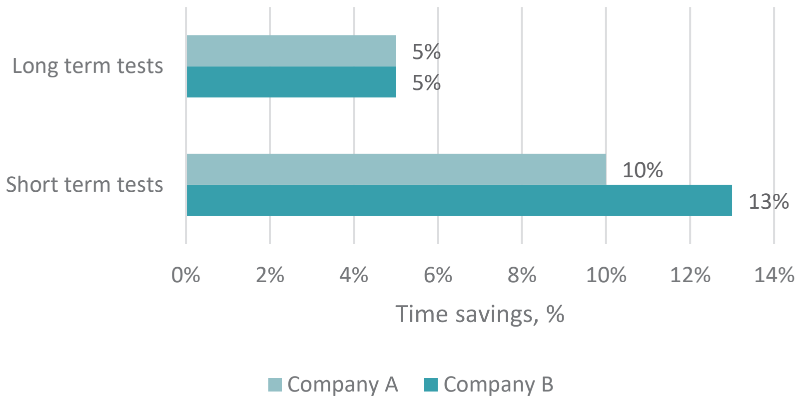


Fig. 43. Time saving results in both companies from short and long term studies

Even if the short term planning shows better outcome results, the focus is to follow the results of long term replanning. Since SMEs normally cannot plan precisely in the short term due to high dynamics, the results of a few-day period replanning yields a higher percentage based on their less accurate initial planning. This was confirmed with both of the companies.

4.6. Long Term Decision Support[5]

These automated production adjustments not only provide immediate responses to the current situations, but also serve as potential recommendations for future enhancements. The data collected has the potential to yield valuable insights for the development of future strategic actions. This becomes a topic for future research, by exploring how this method can not only function in a day-to-day context but also generate sufficient data for effective management decision-making. The gathered data has the potential to identify areas requiring technological equipment upgrades or the development of employee skills and training plans.

During the modeling of various potential scenarios, the program was triggered 200 times. Given that the company operates in three shifts and the program is activated with each update on equipment, materials, or the employee status, reaching 200 activations would typically occur over a span of approximately 2 months. The outcomes of this test, which reveal the frequency of employee absences, are illustrated in Fig. 44.

Based on this data, the company's findings indicate that Employees No. 3 and No. 15 were absent for a total of 17 times out of 200 working days. Employee No. 3, who is a welder, possesses specialized skills, and there are only a few options to replace this employee. The data revealing that this employee was absent on almost 10% of the working days over two months may signal the necessity for strategic

[5] The material in this section has previously been published in [132]

adjustments. Furthermore, additional statistics have been generated to illustrate the frequency of employee replacements, as depicted in Fig. 45.

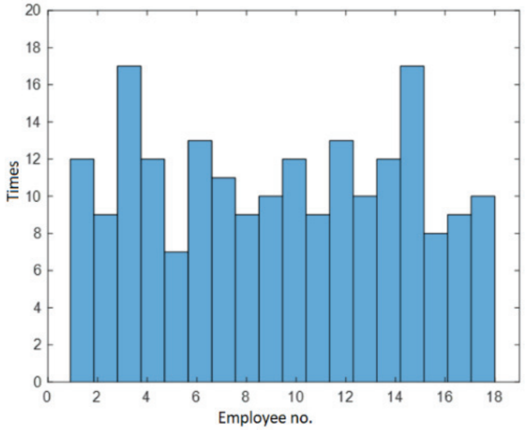


Fig. 44. Numbers of absences in Company A after 200 cycle generations

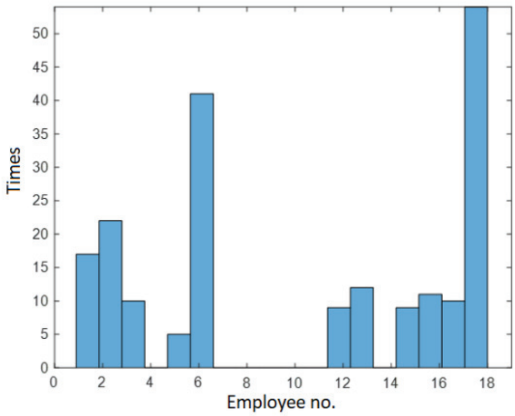


Fig. 45. Numbers of times when an employee replaced employee in Company A after 200 cycle generations

This data reveals that Employee No. 18 was involved in approximately 25% of all cases. Originally, this employee was designated for the cutting operation. However, even though there were seven other employees available during these test runs, no replacements were made. It is essential to investigate the reasons behind this and assess whether the employees' inability to switch to other tasks is due to a lack of knowledge in those operations, which might signal the need for training. Such training could alleviate the workload of Employee No. 18, thus allowing the cutting operation (which is the initial production step) to proceed without interruptions. Additionally, it is possible that this employee was covering other tasks because they were in reserve, possibly due to a lack of equipment or materials. In such cases, alternative solutions should be considered.

The same examination was made with Company B. The results of absences show that, in 200 generations, the distribution is mostly similar between all employees. It stems from the small amount of employees (Fig. 46). However, the results of changes suggest that the biggest number of changes were made involving Employee No. 1 (Fig. 47).

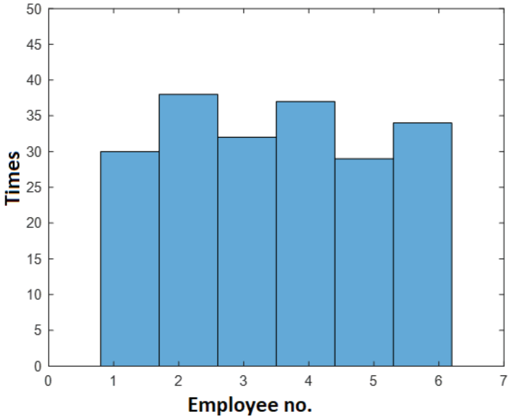


Fig. 46. Numbers of absences in Company B after 200 cycle generations

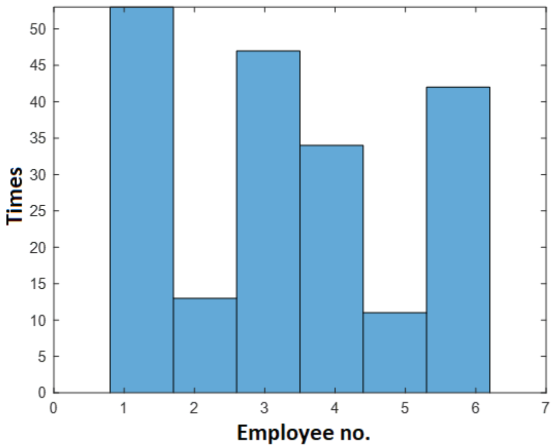


Fig. 47. Numbers of times an employee replaced an employee in Company B after 200 cycle generations

Even with access to such statistics, it remains challenging to predict future interruptions or absences. This underscores the importance of implementing DSM to address this issue. Each day presents unique circumstances, thus highlighting the dynamic nature of production and the existing challenges faced by SME companies. Without advanced ERP systems, there is currently a lack of accessible solutions to tackle this problem.

4.7. Application of DSM DPP for Energy Consumption Reduction[6]

DSM DPP creates the potential for time savings and, subsequently, energy savings through process reorganization. A detailed three-month production orders observation period demonstrated tangible time savings while using the created DSM DPP – which indicated that approximately 5% of time can be saved. Based on this, changes in the energy usage and CO_2 consumption are decreasing, thus giving extra savings in terms of money and CO_2 footprint.

Energy consumption (E) quantifies the electricity demanded by the total number of machines in the company along the period under study, considering normally two operating modes: *active* and *stand-by*, as Equation (51) reflects:

$$E_s = E_0 - E_{DSM\ DPP}, \qquad (51)$$

where: E_0 – the consumed electricity in a base scenario;

$E_{DSM\ DPP}$ – the consumed electricity after applying DSM DPP.

Energy consumption savings derive in CO_2 emissions reduction (rCO_2), according to the emissivity of the system, as Equation (52) reflects:

$$rCO_2 = g \cdot E_s, \qquad (52)$$

where: g – the emissivity (g CO_2/kWh) of the electricity system.

As the research was made, the metal processing company had a total of six key machinery units which were found to be responsible for consuming the majority of the electrical energy resources:

- An automatic tube cutting machine (M1);
- A CNC turning machine (M2);
- A painting booth (M3);
- Welding machines (4 identical pieces) (M4);
- A wood turning machine (M5);
- A CNC milling machine (M6).

It was imperative to ascertain the power consumption of each machinery unit during not only their active periods, but also the stand-by time. A detailed breakdown of this information can be found in Table 16. Consequently, the amount of electricity consumed was disaggregated based on the machinery utilization within each month. Specifically, the machines were either actively operating or in the stand-by mode during the working hours. Table 17 presents the total electricity consumption during the investigated period.

As presented in Subsection 4.4, the total savings during the observed period starting with the middle of December of 2022, and also including January, February, and March of 2023, was 4 working days which can be converted to 64 working hours based on the fact that the production was running in two shifts of 8 hours each. As the time of operations was not changed, these hours are only saved out of the stand-by time. Production operations remained the same since this method does not influence

[6] The material in this section has previously been published in [138]

the process itself. It only optimizes the sequence of processes, and they are divided into several segments.

Table 16. Active and stand-by power consumption of the main machinery units in Company A

Machinery code	Active power, kW	Stand-by power, kW
M1	4	1.5
M2	7.5	3
M3	15	4
M4	6	1.5
M5	5	1.5
M6	7.5	3

Table 17. Electricity usage by month in Company A from December 2022 to March 2023

Year	Month	kWh
2022	December	14179
2023	January	17866
2023	February	13424
2023	March	15869

The overall time of the active and stand-by hours of machines M1–M6 are summed up throughout the described period. The data is given in Fig. 48.

Since the savings in time in total was 64 working hours, this means stand-by time, which was 1432 hours in total, and which was now reduced by 64 hours, which is a 4.5% lower value. Reduced time displacement is presented in Fig. 49.

The reduction of the stand-by hours for the four-month period under study was derived in a decrease of the electricity consumption, as Figs. 50 and 51 represent. Namely, the total electricity consumption was reduced by 175 kWh after applying DSM DPP. In this regard, the highest electricity reduction corresponded to M2, with a decrease of 86.7 kWh. This situation matched two circumstances: this machine manifests the highest stand-by hours decrease after the DSM DPP application, and it has a relatively high stand-by power consumption (Table 16).

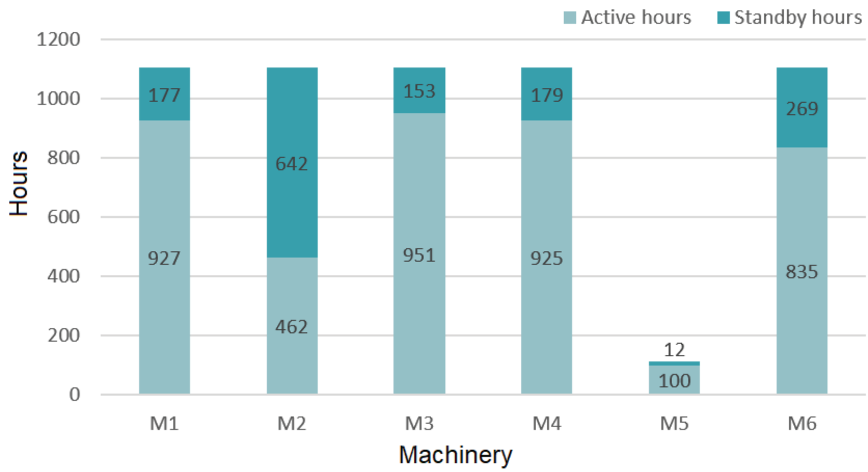


Fig. 48. Active and stand-by hours of machines M1–M6 in Company A during the observed period without DSM DPP adapted

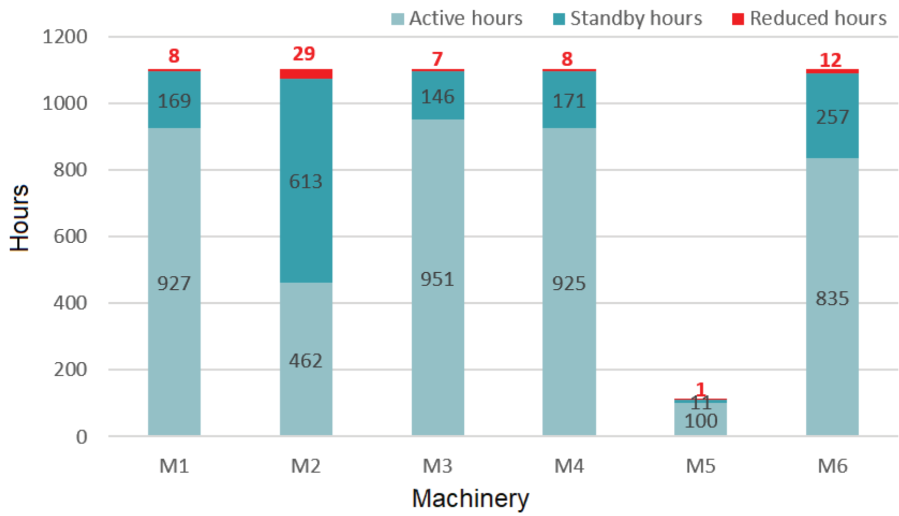


Fig. 49. Active, stand-by and reduced hours of machines M1–M6 in Company A during the observed period with implemented DSM DPP

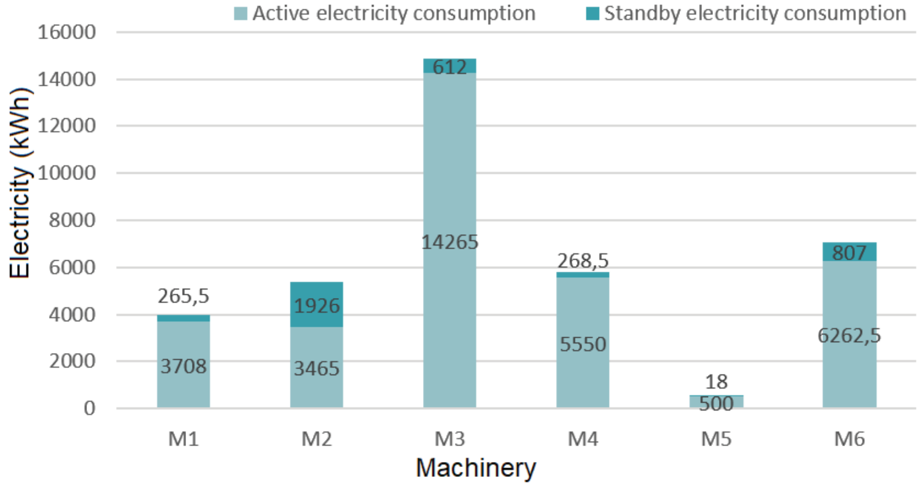


Fig. 50. Active and stand-by electricity consumption of machines M1–M6 in Company A during observed period without DSM DPP adapted

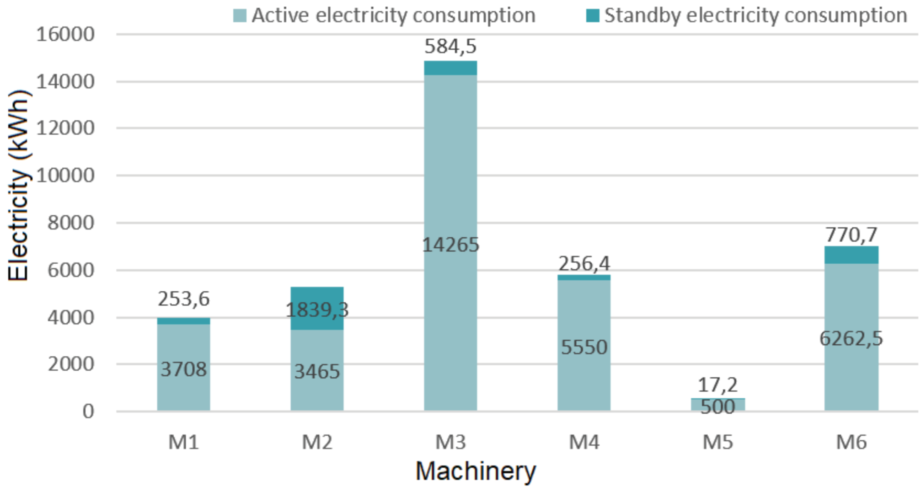


Fig. 51. Active and stand-by electricity consumption of machines M1–M6 in Company A during the observed period with implemented DSM DPP

Furthermore, the company under study is connected to the Lithuanian electricity grid, with an emissivity of 154 g CO_2/kWh [139]. Moreover, nowadays, the company does not include any self-consumption renewable system. Thus, these above-mentioned electricity savings lead to a decrease in the CO_2 emissions of the company due to electricity consumption. Specifically, the CO_2 emissions reduction due to electricity consumption of the six machines after applying DSM corresponded to 27 kg CO_2, compared to the base scenario. All of these savings are based on the electricity consumption and do not include other sources.

4.8. Section Summary and Insights

As seen from the case study researches in the investigated companies, the method was applied in two different companies, one of which was small, and the other was a medium-sized enterprise. This has shown the adaptability and universality of the method. Different industries and final outcomes have been investigated with no specific changes in the method itself. Efficiency was increased either in the production processes which were specified for manufacturing and production, or in the service sector. Thus the possibility and feasibility of implementing this method to the service area has been demonstrated; the method also covers planning issues and is employee-centered. The method is easily adaptable and has important sections as a new item/service implementation subprogram, task priority ranking, or a matrix of skills.

Replanning is unavoidable in the production, especially in SMEs. This type of enterprises is dealing with a large variety of products, small order quantities, and they are mostly using only expert opinion and human power. In response to this issue, DSM DPP was checked in the automotive body repair company having 6 full-time employees, and where 9 different operations are performed. Examinations of 3 months and 3 days were performed. A 3-month-long test showed that, by using this specific method, the company can save up to 5% of the production time as it could have potentially achieved a reduction from 72 to 68 working days. 3-day planning tests were conducted, and the results showed that the planned orders could be performed based on the generated sequence to achieve better performance. That would lead to time savings from 24 to 20–21 working hours while performing the same orders. On top of that, the method was checked in a metal processing company with a 3-month observation and a short-term observation of 3 days. Both observations showed savings in time: from 47 hours to 42 hours and from 72 working days to 68 working days. Table 18 summarizes the presented observations.

Table 18. Summary of performed tests in the research

	24 hours observation	**3 months observation**	**3 days observation**	**Test of 200 cycles**
Company A	47 -> 42 hours	72 -> 68 w. d.	-	+
Company B	-	72 -> 68 w. d.	24 -> 20 hours 24 -> 21 hours	+

This method also highlights the importance of data collection, and, based on long-term statistics collected on a daily basis, the company can agree on future decisions. This is an additional advantage of DSM DPP which is based on data collection and analysis. This method provides another benefit, specifically, energy savings, which follows up with reduced emissions of CO_2. The study showed that, in Company A, it leads to a decrease of 27 kg CO_2 emissions during 4 months of observation due to a reduction of electricity consumption compared to the base scenario where no method is applied.

5. RECOMMENDATIONS

5.1. Introduction

This method is universal and can be easily used in various manufacturing SMEs. An SME group can cover a wide range of companies differing in size, the production site, and the final product. As these companies are mostly employee-centered, the method stands for a virtual production manager and responds to dynamic production processes. This prevents human error, a biased view, or a delayed response. The statistics might be used to make strategic decisions about the improvement to the machinery, the training of employees, etc. As an outcome, quality issues might be solved with this method (assigning tasks based on a matrix of skills). DSM DPP is concentrated for SMEs since large companies mostly have implemented different types of systems for monitoring their manufacturing processes.

This section provides the respective recommendations for using this method.

5.2. Appropriate Use of the Method

This method was specifically developed with a focus on SMEs as its primary target. Consequently, the method exhibits adaptability and suitability for implementation across companies of varying sizes, including larger organizations. However, it is important to note that the identified problems and objectives addressed in this study primarily stem from the SME sector. This sector covers companies with a high number of unique, niche products and no mass production or even merely one-piece orders. Such productions are the most time-consuming in the industry, and lack of optimization is prevalent since no repeated sequence can be adapted. Moreover, these industries may be characterized as human-centric, given that a significant proportion of the workforce is reliant on manual labor. Consequently, the development of a production plan tailored to the individual skills and knowledge of employees emerges as a pivotal measure contributing to the company's sustainability, where the social responsibility stands as one of the three factors of sustainability. Considering this, the applicability of this method in the context of large-scale mass production companies, characterized by advanced technologies and distinct production tracking systems, may be limited. Nevertheless, empirical testing has confirmed its efficacy in production companies offering both end products and services. With minor adjustments, the method holds potential for utilization across a broad range of companies. Furthermore, the method's ease of application, without necessitating significant changes in data acquisition or the modernization of production systems, highlights its practicality, particularly in the light of the research findings on the already existing tools. As the outcome of this method is efficiency in time, profit and energy, this results in its use in various companies. Irrespective of a company's primary objectives and strategic priorities, whether centered on reducing the energy consumption, enhancing the product quality, or expediting production cycles, this method effectively addresses these concerns either directly or as a consequential outcome. Consequently, the adoption of this method contributes to the realization of additional facets of a company's sustainability, encompassing economic and environmental dimensions. Optimizing resource utilization translates into economic advantages for a company, thereby encompassing increased profitability, reduced resource consumption, and expedited production processes. Simultaneously, time-saving aspects of this method manifest in energy conservation, which leads to ecological benefits as it aids in mitigating a company's environmental footprint and waste generation. DSM DPP applies in covering not only different sectors, but even different problems between countries and economies. While one sector can specify on saving the production time, another sector might want to save energy or human resources. The whole process is based on multicriteria assessment so that to increase its range of usage and demand for it.

5.3. Automation of Production Manager

I4.0 has revolutionized production processes through the implementation of robotics, particularly by targeting tasks at the lowest operational level which entail repetitive movements and do not demand specific expertise or responsibilities. This approach has effectively eliminated employee-based models, thus creating a more stable manufacturing environment. Nevertheless, the need for higher-level production management still remains unresolved. The created method can be regarded as a 'virtual production manager' as it generates responses which typically arise from the production manager following expert evaluations. The necessity for such assistance in this role became evident during critical situations when it was imperative to minimize the human contact. Based on this method, the higher value work time is saved by this virtual assistant. Thus DSM DPP not only replans production, provides data for long-term decisions, but also saves time of higher-class employees. On top of that, human error and impartiality is eliminated with this method – as the matrix of skills provides information about skills in each operation; thus a person with insufficient skills will not be assigned to perform a task causing any unacceptable deviations in production. Various factors involved in the rapidly changing production must be evaluated, which overloads experts and might be missed due to the human factor.

5.4. Method Usage for Long-Term Decisions

By employing this method, companies can formulate long-term plans based on the obtained results. The analysis of a specific case study at the end of Subsection 4.4 provides valuable insights into potential long-term improvements. Integrating real-time response and replanning strategies with future enhancements enables businesses to achieve success and operational efficiency. Traditional production planning systems often lack adequate data and statistics. In contrast, this method demonstrates how past performance outcomes can be utilized to evaluate and optimize future plans. Merely optimizing production in real-time yields only marginal improvements, whereas incorporating long-term decisions can propel a company to a new level of performance. Notably, the method is available to effortlessly collect and present data on actual production processes, and this serves as robust evidence when assessing the necessity of investments and mitigating uncertainties.

CONCLUSIONS

1. A well-defined and suitable research methodology tailored specifically to the domain of manufacturing engineering within Small and Medium-sized Enterprises has been meticulously established to ensure the effective and efficient execution of the research objectives. The deficiency of methods specified for employee-centered SMEs and the need for a solution due to the highly dynamic production environment has been stated. The research identifies the common problems encountered in production processes and formulates a method based on these findings.
2. The Decision Support Method for Dynamic Production Planning has been created and implemented to increase the efficiency of production processes while focusing on the critical performance metrics, namely, time and the production cash flow, which are susceptible to fluctuations caused by dynamic production challenges such as employee absenteeism, machinery breakdowns, and sourcing disruptions. Empirical assessments have been conducted within the operational contexts of two distinct manufacturing enterprises, which allowed for the comprehensive evaluation of the method's efficacy and resulted in time savings in the production processes.
3. The method has been created and presented in *Matlab* as a working virtual production assistant which replans production in quasi-real-time. Multiple data arrays have been generated to facilitate the implementation of the created method: skill sets of employees, machine parameters, task priority rankings, hourly costs associated with machinery and employees, etc. Based on the accrued information, short-term examination based on historical data of 24 hours (3 shifts), long-term examination based on the historical data of 3 months, short-term future examination of 3 days and repeated cycle tests have been performed, which made up 7 unique studies in total.
4. Simulation of production processes with real data from certain manufacturing companies has been performed. Two distinct companies were involved in the experiment. They represented different sizes and production domains to demonstrate the universality of the approach. The first examined company was a metal processing company specializing in the production of furniture components. The 24-hour investigation with real historical data resulted in 10% time savings, while a 3-month examination based on historical data showed 5% time savings. The second company was an automotive body repair service provider catering to individual clients. Tests of 3-month data resulted in 5% time savings of time, while 3-day future tests led to 10–15% time savings.

6. SANTRAUKA

6.1. Įvadas

Temos aktualumas

Ketvirtoji pramonės revoliucija pakeitė ne tik gamybos sektorių, bet ir tradicinę verslo aplinką. Įmonėms atsiranda būtinybė kurti sistemingus planus, kad sumažintų išlaidas, efektyviai išnaudotų savo resursus ir atitiktų rinkos paklausą. Naujausi technologiniai atradimai suteikia galimybę pasiekti ir analizuoti duomenis, modernizuoti gamybos procesus, įdiegti automatizavimą ir robotizavimą. Tačiau šios pažangiausios technologijos ne visada yra lengvai ir greitai įgyvendinami sprendimai smulkaus ir vidutinio verslo įmonėse, kuriose dažnai pritrūksta reikiamų finansinių išteklių, specifinių kompetencijų ar resursų atlikti naujinimus. Nepaisant to, kad šio sektoriaus įmonių grupių svarba ekonomikoje itin didelė, jos kasdien susiduria su iššūkiais ir yra priverstos siekti vis geresnių rezultatų. Atlikus tyrimą, buvo nustatyta, kad dažniausiai pasikartojančių trikdžių grupės yra trys – darbuotojų nebuvimas darbe, žaliavų trūkumas ir mechanizmų gedimai. Gamybos optimizavimas šioms įmonėms yra ypač svarbus, nes dažniausiai yra gaminami smulkiaserijiniai ar vienetiniai gaminiai, tad reikia kompensuoti prarandamą laiką dėl individualiems poreikiams pritaikytų gamybos procesų ir riboto automatizuotų gamybos metodų naudojimo. Kita šių įmonių ypatybė yra ta, kad jos ypač orientuotos į darbuotoją ir žmogiškasis faktorius yra itin svarbus, nes žinios, darbo jėga ir sprendimų priėmimas daugiausia priklauso nuo eksperto nuomonės. Atsižvelgiant į tai, kad smulkaus ir vidutinio dydžio įmonės orientuojasi į mažų partijų ar nišinių produktų gamybą, šios įmonės užsiima dinamišku gamybos planavimu, siekdamos prisitaikyti prie kintančių reikalavimų viso gamybos proceso metu. Dažnai perplanavimui reikia greito sprendimo, bet tai padaryti sunku dėl didelio kintamųjų skaičiaus. Įsigilinus į šiuos faktus tampa akivaizdu, kad, norint išlikti konkurencingoms rinkoje, įmonėms reikia patogaus, prieinamo ir lengvai adaptuojamo įrankio, teikiančio sprendimus ir pasiūlymus realiu laiku vykdomiems gamybos scenarijams.

Atsižvelgiant į pirmiau minėtus iššūkius, su kuriais susiduria smulkaus ir vidutinio dydžio įmonės, šiuo tyrimu siekiama pasiūlyti sprendimą, leidžiantį planavimą atlikti efektyviau ir greičiau. Sukurtas naujas metodas, vadinamas sprendimų priėmimo metodu dinaminiam gamybos planavimui. Skirtingai nuo tradicinių metodų, reikalaujančių didelių gamybos procesų pakeitimų, šis metodas yra praktiškas sprendimas sekti ir adaptuoti gamybos planavimą, nereikalaujant didelių investicijų, ir yra paremtas daugiakriteriu vertinimu. Metodas renka ir naudoja ne tik informaciją apie techniką ar žaliavas, bet ir darbuotojo kompetencijas. Tai svarbi jo dalis, nes vis dažniau kalbama apie penktąją pramonės revoliuciją, kurioje vyrauja orientacija į žmogų, tvarumas ir gebėjimas greitai atnaujinti darbą po iškilusių nesklandumų. Metodas taip pat vertina užduočių svarbą, atliekami kelių laipsnių patikrinimai. Įdiegusios šį metodą, įmonės gali operatyviai spręsti gamybos procesų stabdymus, atsiradusius dėl tokių veiksnių, kaip darbuotojų nebuvimas, medžiagų trūkumas, mašinų gedimai ar naujo produkto gamybos procesų neapibrėžtumas. Šis metodas priklauso nuo beveik realiojo laiko duomenų, leidžiančių įmonėms nedelsiant gauti atsakymus ir imtis atitinkamų veiksmų, kad sumažintų gamybos stabdymus ir veikla būtų optimizuota. Algoritmais yra atspindimas visas gamybos procesas, vykdomas planavimas, kurio užduotis yra patenkinti tikslo funkciją. Ši funkcija paremta daugiakriteriu vertinimu ir siekia gamybai reikiamo laiko minimumo, gaunamo pelno maksimumo bei energetinių resursų minimumo. Remiantis šiais pagrindiniais faktoriais, įvairaus profilio įmonės gali pritaikyti šio metodo optimizavimą.

Šioje disertacijoje pateikiamas ne tik analitinis sprendimų priėmimo metodas dinaminiam gamybos planavimui, bet ir jo matematinis modelis. Siekiant įsitikinti modelio veiksmingumu, jis buvo išbandytas rankiniu ir automatiniu būdu. Automatiniai testai buvo suprogramuoti ir atlikti Matlab programa. Norint užtikrinti, kad sukurtas metodas būtų pritaikomas universaliai, skirtingi tyrimai buvo atlikti dviejose gamybos įmonėse, kurios patenka į smulkaus ir vidutinio dydžio kategoriją. Tyrimams buvo naudoti realūs nuasmeninti duomenys, gauti iš dviejų įmonių – viena įmonė užsiima metalo apdirbimu, o kita teikia automobilių kėbulų remonto paslaugas. Šiais tyrimais buvo siekiama įrodyti metodo pritaikomumą ir universalumą įvairiose pramonės šakose, kai skiriasi darbo specifika, operacijos, apkrovimai, galutinis produktas. Šios pramonės šakos buvo pasirinktos taip, kad atitiktų įvairius gamybos scenarijus ir iššūkius, su kuriais dažnai susiduria nagrinėta įmonių grupė. Analizė apėmė skirtingų gamybos užsakymų modeliavimą ir rezultatų įvertinimą proceso trukmės ir pelno požiūriu. Atlikti trijų tipų tyrimai – naudojant trumpalaikius ar ilgalaikius praeities, naudojant trumpalaikius duomenis ateities gamybos perplanavimui. Visais atvejais nustatytas teisingas metodo veikimas bei gamybos procesų optimizavimas. Sukurtas metodas nesutrumpina atliekamos operacijos laiko, bet perskirsto gamybos planą taip, kad užsakymai būtų atliekami efektyviai ir nuosekliai, įvertinant įvairius veiksnius – darbuotojų įgūdžius, valandines technikos sąnaudas, energetinį rezultatyvumą ir kt. Taip mažinamas laikas, kurio metu gamyba yra neapkrauta, resursai neišnaudojami. Taip pat šio metodo kaupiama informacija leidžia rinkti duomenis, kurie būtų naudojami planiniams gamybos pakeitimams.

Šis metodas apima kelias tarpdisciplinines technologijos mokslų sritis. Jis prasideda nuo gamybos proceso modeliavimo, kuris patenka į gamybos inžinerijos sritį, ir apima įvairias mechanikos inžinerijos šakas (52 pav.).

Darbo tikslas

Sukurti beveik realiu laiku veikiantį sprendimų priėmimo metodą dinaminiam gamybos planavimui siekiant padidinti gamybos procesų efektyvumą.

Uždaviniai

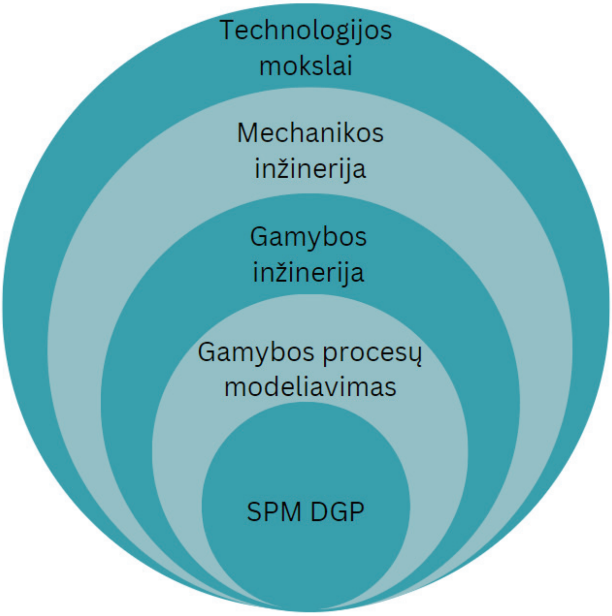
Siekiant įgyvendinti užsibrėžtą šio darbo tikslą, buvo iškelti šie uždaviniai:

1. Apibrėžti tinkamą tyrimo metodiką gamybos inžinerijos kontekste, pritaikytą smulkaus ir vidutinio dydžio įmonėms.
2. Apibrėžti, nurodyti ir išspręsti beveik realaus laiko gamybos procesų efektyvumo optimizavimą.
3. Sukurti kompiuterizuotą sprendimų priėmimo metodą dinaminiam gamybos planavimui smulkiose ir vidutinėse įmonėse.

4. Įvertinti ir įrodyti siūlomo metodo tinkamumą, atliekant realių gamybos duomenų modeliavimą.

Mokslinis naujumas

1. Sukurta nauja matematinė tikslo funkcija, leidžianti padidinti gamybos procesų efektyvumą smulkaus ir vidutinio dydžio įmonėse.
2. Sukurtas naujas sprendimų priėmimo metodas dinaminių gamybos procesų planavimui smulkaus ir vidutinio dydžio įmonėse.
3. Šis tyrimo metodas sukurtas į darbuotojus orientuotoms įmonėms, kas itin aktualu I5.0 kontekste, kol dauguma tyrimų yra sutelkti tik į įrangą ir medžiagas.



52 pav. Sprendimų priėmimo metodo dinaminiam gamybos planavimui pozicija technologijos moksle

Praktinė darbo vertė

Smulkių ir vidutinių įmonių svarba bendrai ekonomikai yra itin didelė, tačiau jos susiduria su sunkumais diegdamos naujausias technologijas savo gamybos procesuose, o greiti ir dinamiški gamybos procesai bei į darbuotojus orientuotas pobūdis rodo poreikį pateikti veiksmingą, bet lengvai pritaikomą ir įgyvendinamą gamybos planavimo priemonę. Šioje disertacijoje sprendžiama dinaminio gamybos planavimo problema, ji išspręsta sukurtu sprendimų priėmimo metodu momentiniam dinaminiam gamybos perplanavimui.

Ginamieji teiginiai

1. Šioje disertacijoje sukurtas naujas sprendimų priėmimo metodas dinaminiam gamybos planavimui ir įrodyta jo reikšmė didinant gamybos procesų efektyvumą.
2. Remiantis metodu sukurtos tikslo funkcijos optimizavimo užduotims – laiko sąnaudų minimizavimo ir gamybos apimčių maksimizavimo.

Darbo aprobavimas

Disertacijos rezultatai pristatyti 5 tarptautinėse ir 5 nacionalinėse konferencijose, publikuoti 4 moksliniuose straipsniuose įvairiuose tarptautiniuose žurnaluose (Web of Science citavimo indeksą turinčiuose žurnaluose), publikuoti 3 konferencijų pranešimų medžiagose tarptautinėse mokslo duomenų bazėse.

Disertacijos struktūra

Disertaciją sudaro šie skyriai: įvadas, literatūros apžvalga, metodai, tyrimai, rezultatai, rekomendacijos ir išvados, po kurių pateikiama santrauka lietuvių kalba, literatūros sąrašas ir autoriaus mokslinių publikacijų ir konferencijų pranešimų sąrašas. Disertacijos įvade pateikiama pagrindinė darbo idėja ir motyvacija, pagrindinis darbo tikslas ir uždaviniai, disertacijos naujumas ir svarba, pagrindiniai gynimo teiginiai. Disertacijos pabaigoje pateikiamas literatūros sąrašas, publikacijų ir konferencijų pranešimų sąrašas. Iš viso disertaciją sudaro 154 puslapiai, 89 formulių, 77 paveikslai ir 24 lentelių. Literatūros sąrašas susideda iš 139 šaltinių.

6.2. Smulkaus ir vidutinio dydžio įmonių dinaminio gamybos planavimo metodų ir analitikos apžvalga

6.2.1. Smulkaus ir vidutinio dydžio įmonių svarba gamybos sektoriuje

Smulkiam ir vidutiniam verslui (SVV) yra priskiriama didžioji dalis gamybos įmonių. Tačiau, atsižvelgiant į technologinius pokyčius, kurie neabejotinai susiję su Pramone 4.0, SVV nėra palankioje padėtyje, nes technologinės transformacijos procesas kelia įvairių kliūčių dėl esamo darbo pobūdžio. Pramonės pažanga ir naujausios technologijos, tokios kaip daiktų internetas, debesų kompiuterija, didieji duomenys, robotika, dirbtinis intelektas, 3D spausdinimas ir kt. suteikia pramonei galimybę padidinti efektyvumą, tobulinti procesus ir kurti naujoviškus produktus bei paslaugas. Tačiau SVV susiduria su kliūtimis diegdamos skaitmenines technologijas. Norint įveikti šiuos iššūkius, labai svarbu skatinti SVV naudoti naujausius technologinius sprendimus, kad jos galėtų pasinaudoti skaitmeninės ekonomikos teikiama nauda [3].

SVV yra esminis pasaulio ekonomikos elementas, darantis didelę įtaką užimtumui, inovacijoms ir ekonomikos augimui. Pagal naujausią Europos Komisijos parengtą SVV apibrėžties naudotojo vadovą (2020 m. spalio mėn.), labai mažos įmonės įdarbina mažiau nei 10 darbuotojų, o jų metinė apyvarta arba balanso suma neviršija 2 mln. eurų. Mažose įmonėse dirba mažiau nei 50 darbuotojų, o jų metinė apyvarta arba balanso suma neviršija 10 mln. eurų. Vidutinėse įmonėse dirba mažiau nei 250 darbuotojų, o jų metinė apyvarta neviršija 50 mln. eurų arba metinis balansas neviršija 43 mln. eurų [3].

2021 m. Europos Sąjungos valstybėse narėse veikė apie 22,8 mln. smulkių ir vidutinių įmonių, kurios sudarė 99,8 % nefinansinio verslo sektoriaus įmonių [1] iš visų įmonių ir užtikrino maždaug du trečdalius visų darbo vietų. Kalbant apie gamybą, SVV dažnai specializuojasi nišinėse rinkose arba konkrečiose produktų linijose ir gali labai lanksčiai reaguoti į paklausos ar rinkos sąlygų pokyčius [5]. Toks lankstumas ir gebėjimas reaguoti gali būti ypač svarbus šiuolaikinėje sparčiai kintančioje verslo aplinkoje, kurioje bet kada gali atsirasti naujų technologijų ir naujų konkurentų. Be to, šio tipo įmonės yra svarbios inovacijų požiūriu, nes jos paprastai yra inovatyvesnės ir lankstesnės nei didesnės įmonės. Jos dažnai yra didesnių įmonių tiekėjos arba subrangovės, teikiančios specializuotas dalis arba paslaugas. Tačiau nors jos gali greitai prisitaikyti prie vartotojų poreikių, gamybos priemonių pritaikymas, modernizavimas ir automatizavimas vis tiek reikalauja didelių finansinių ir žinių pajėgumų.

SVV sėkmę Europoje lemia gebėjimas gaminti įvairiapusiškai, palaikyti glaudžius ryšius su klientais ir greitai reaguoti į besikeičiančius rinkos poreikius bei individualius klientų pageidavimus [6].

6.2.2. Smulkaus ir vidutinio dydžio įmonių patiriami sunkumai, integruojant naujausias technologijas

Pastaruosius du dešimtmečius mokslininkai ir valstybinės institucijos Europoje ir visame pasaulyje analizuoja gamybos įmonių pažangą siekiant adaptuoti Pramonės 4.0 potencialą ir pažangą. Šis įmonių atsinaujinimas suvokiamas kaip perėjimo iš dabartinės gamybos ir paslaugų pramonės būklės į naująjį amžių. Tačiau tiek skaitmeninimas, tiek automatizavimas kelia iššūkių žmogiškajam faktoriui gamyboje ir SVV gamybos linijoms, kurios lėtai arba visai nepajėgia atlikti technologinio perėjimo. Šios įmonės dažniausiai susiduria su šiomis problemomis: kvalifikuotų darbuotojų paieška ir supratimo apie galimą modernizacijos naudą stoka [10], didelės išlaidos, techninių žinių trūkumas, susirūpinimas dėl duomenų saugumo [11] ir kt. Taip pat viena iš pagrindinių problemų, kurias nurodo [12], yra aiškios automatizavimo strategijos nebuvimas ir sunkumai nustatant konkrečius poreikius atitinkančius automatizavimo sprendimus. Tai patvirtina ir Yu ir Schweisfurth – žinios apie technologiją ir laukiama jos nauda buvo reikšmingi veiksniai, susiję su I4.0 technologijų diegimu [13]. Mittal ir kt. sutinka, kad SVV žengti į I4.0 yra sunku ne tik dėl lėšų trūkumo, bet ir dėl ekspertų žinių stokos. Jis teigia, kad dėl kintamųjų skaičiaus gamyboje šis procesas tampa dar sudėtingesnis ir gali būti nepasiekiamas be išorinių ekspertinių žinių [14].

6.2.3. Dažniausi inžineriniai sprendimai SVV: daiktų internetas, didžiųjų duomenų analizė, dirbtinis intelektas

Nors, kaip aptarta anksčiau, yra įvairių kliūčių, susijusių su SVV įmonių gamybos perkėlimu į I4.0, neabejotinai yra ir įvairių privalumų. Tiek akademinė bendruomenė, tiek verslas sutinka, kad, siekiant didesnio konkurencingumo su didelėmis įmonėmis ar užsakomųjų paslaugų bendrovėmis, šis perėjimas yra neišvengiamas. Šiame skyriuje aptariami dažniausiai pasitaikantys technologiniai metodai, kuriuos SVV pritaiko arba turėtų pritaikyti ateityje.

Daiktų internetas paplitęs visuose technologiniuose sektoriuose, o tai lemia pasaulinė interneto tinklų plėtra, suteikianti plačią prieigą prie išmaniųjų prietaisų – nuo namų iki pramonės įmonių. Jis pripažįstamas kaip virtualiai tarpusavyje sujungtų išmaniųjų įrenginių tinklas, kuriuo siekiama sudaryti sąlygas bendram, decentralizuotam užduočių vykdymui tarp įvairių išmaniųjų įrenginių, dėl to greičiau įvykdomos užduotys, supaprastinama stebėsena, priežiūra ir automatizavimas [16, 17]. Pramonės kontekste išmanieji komponentai, pavyzdžiui, jutikliai ir pavaros, integruojami į įrenginius, skatina pramonės transformaciją, įgalina mašinų tarpusavio ryšį ir automatizavimą [18]. Tokia technologija vadinama daiktų gamykla (angl. *Factory of Things,* FoT) arba pramoniniu daiktų internetu (angl. *Industrial Internet of Things*) gamyboje. Tai išplečia daiktų interneto principus, kad būtų patobulintos gamybos sistemos, optimizuotas efektyvumas, sutrumpintas pateikimo rinkai laikas ir padidintas lankstumas pagal Pramonės 4.0 ir išmaniosios gamybos koncepcijas [19].

Didžiųjų duomenų analizė ir dirbtinis intelektas iš esmės keičia gamybos veiklos principus. Rinkdama ir analizuodama duomenis iš įvairių šaltinių, įskaitant jutiklius ir tiekimo grandinės partnerius, didžiųjų duomenų analizė leidžia nustatyti veiklos modelius ir tendencijas, optimizuoti procesus ir sumažinti atliekų kiekį. Sumažėjus atminties sąnaudoms ir padidėjus duomenų perdavimo greičiui, tapo įmanoma surinkti didelius kiekybinių jutiklių sistemų duomenų kiekius [32]. Didelių duomenų analizė (DDA) yra esminis Pramonės 4.0 komponentas, leidžiantis gamybos procesuose panaudoti duomenis iš įvairių šaltinių.

6.2.4. Skaitmeninio dvynio konceptas gamybos procesams

SVV dažnai susiduria su sunkumais, kai jų gamybos poreikiams tenkinti reikia pritaikyti skaitmeninio dvynio (SD) technologijas. Viena pagrindinių kliūčių – užtikrinti SD tikslumą atvaizduojant fizinę sistemą, kurią jis turi modeliuoti, o tam reikia rinkti, apdoroti ir analizuoti didelius duomenų kiekius. Kitas iššūkis – nėra visuotinai standartizuoto keitimosi duomenimis formato. Taip pat būtinas nuolatinis ir patikimas patikrintų ir patvirtintų duomenų srautas tarp fizinių ir skaitmeninių atitikmenų. Integracija su įprastinėmis gamybos sistemų mašinomis gali apriboti SD paslaugų galimybes. Kiti sunkumai – lėtas duomenų gavimo gamybos sistemose standartizavimas, didelės naujos IT aplinkos sąnaudos ir būtinybė ugdyti naujus įgūdžius bei keisti žmonių vaidmenis. Tačiau debesijos paslaugų ir iš anksto parengtų programinės įrangos programų diegimas gali suteikti potencialios naudos. Skaitmeninis dvynys taip pat gali integruoti darbuotojus į kompiuterinius sprendimų priėmimo procesus, iš karto teikdamas vietinę informaciją apie dabartinį darbuotojo tvarkaraštį, pageidavimus, įgūdžius ir patirtį. Duomenų generavimo ir saugojimo pažanga, algoritmai ir besikeičiantys gamybos rinkos poreikiai paskatino pereiti nuo tradicinio imitacinio modeliavimo prie labiau į duomenis orientuoto požiūrio [2]. Dažniausiai naudojami fiziniai modeliai, tačiau turint daug duomenų skaitmeninių dvynių kontekste išpopuliarėjo duomenimis grindžiamas modeliavimas. Tai palengvina atvirojo kodo bibliotekos, tokios kaip TensorFlow, Torch ir OpenAI, ir lengvai prieinami aukštos kokybės mokymo ištekliai. Pažangių mašininio mokymosi algoritmų, tokių kaip gilieji neuroniniai tinklai ir Gauso procesai, kūrimas prisidėjo prie pastarojo meto skaitmeninių dvynių technologijų plėtros. Šiuos algoritmus galima lengvai naudoti modeliui atnaujinti ir ateities prognozėms atlikti.

6.2.5. Gamybos stebėjimas ir planavimas realiuoju laiku (gamybos laiko koregavimas)

Gamybos stebėjimas realiuoju laiku, paremtas pažangiomis technologijomis ir duomenų analize, teikia didelę naudą smulkaus ir vidutinio dydžio įmonėms, nes leidžia iš karto gauti išsamią informaciją apie gamybos procesus. Tai leidžia stebėti ir kontroliuoti gamybos etapus realiuoju laiku, didinti veiklos efektyvumą, kokybės valdymą ir išteklių optimizavimą. Įmonė gali stebėti tokius pagrindinius rodiklius, kaip gamybos našumas, ciklų trukmė, mašinų prastovos ir atsargų lygis, nustatyti kliūtis, racionalizuoti veiklą ir priimti duomenimis pagrįstus sprendimus. Turėdami sekimą realiuoju laiku, verslai gali aktyviai spręsti problemas, mažinti švaistymą, didinti našumą, didinti klientų pasitenkinimą ir įgyti konkurencinį pranašumą.

Gamybos įmonės dažnai susiduria su iššūkiais, kai reikia stebėti visą gamybą, nes naudojamos skirtingos ir įvairių gamintojų mašinos. Vienos sekimo sistemos palaikymas gali būti sudėtingas ir brangus, ypač kai gamybos linijos nuolat optimizuojamos ir perprojektuojamos, siekiant pagerinti jų našumą [62]. Tačiau, norint veiksmingai sekti gamybos parametrus, pavyzdžiui, gamybos apimtis, darbo laiką ir kitus pagrindinius veiklos rodiklius, reikia didelės sekimo skiriamosios gebos.

Dėl netinkamos sekimo rezoliucijos gali atsirasti netikslių ir nepakankamų sekimo ataskaitų, kurios gali trukdyti optimizavimo procesui. Nors daugelis gamybos įmonių naudojamų mašinų yra su įrengtomis operacijų sekimo funkcijomis, SVV vis dar dažnai naudojasi senesnėmis mašinomis, kuriose tokių funkcijų nėra. Visapusiškas gamybos sekimas įmonėms yra iššūkis dėl įvairių mašinų tipų, todėl, norint gauti tikslias optimizavimo ataskaitas, ypač SVV, turinčioms senesnes mašinas, kurioms trūksta sekimo funkcijų, būtina ekonomiška didelės skiriamosios gebos sistema.

6.2.6. Optimizavimo užduočių skaičiavimai gamyboje

Optimizavimo užduočių skaičiavimai apima efektyviausio būdo norimam produktui pagaminti nustatymą, atsižvelgiant į įvairius veiksnius, pavyzdžiui, laiką, sąnaudas, kokybę ir išteklius. Šiuos skaičiavimus galima atlikti taikant įvairius optimizavimo metodus, įskaitant matematinį modeliavimą, imitavimą ir dirbtinį intelektą. Automatizavimas atlieka svarbų vaidmenį optimizuojant gamybos procesus, nes jie apima mašinų, įrankių ir automatizavimo sistemų, padedančių racionalizuoti ir automatizuoti įvairias su gamyba susijusias užduotis, projektavimą ir kūrimą. Šios sistemos paprastai sukuriamos siekiant sumažinti žmogaus klaidų skaičių, padidinti efektyvumą ir produktyvumą.

Optimizavimo užduotys – tai efektyviausių ir veiksmingiausių sudėtingų gamybos uždavinių sprendimų paieška, siekiant maksimaliai padidinti našumą, sumažinti sąnaudas ir pagerinti bendrą efektyvumą. SVV, kurios dažnai veikia turėdamos ribotus išteklius ir susiduria su aršia konkurencija, optimizavimas tampa lemiamu veiksniu siekiant veiklos tobulumo ir siekiant išlikti konkurencingoms rinkoje. Naudojant pažangius matematinius modelius, algoritmus ir skaičiavimo metodus, optimizavimo užduočių skaičiavimai suteikia vertingų įžvalgų apie gamybos procesus, todėl įmonės gali priimti pagrįstus sprendimus dėl išteklių paskirstymo, tvarkaraščių sudarymo, atsargų valdymo ir pajėgumų planavimo. Zhang Y. siūlo gamybos užduočių planavimo pažangiuoju būdu metodą, kuris atsižvelgia į daugybę apribojimų, pavyzdžiui, užduoties prioritetą, laiko apribojimus ir skubų užduoties įterpimą. Tikslas – minimizuoti laukimo laiką ir užbaigimo laiką, uždaviniui spręsti taikant BAS (angl. *Beetle Antennae Search*) algoritmą (Zhang, Xu, Huang ir Xiao, 2023).

6.2.7. Skyriaus išvados ir problemų formulavimas

Šiame skyriuje nagrinėta smulkių ir vidutinių įmonių (SVV) reikšmė gamyboje ir jų iššūkiai diegiant Pramonės 4.0 technologijas. Nepaisant kliūčių, su kuriomis susiduriama diegiant šias technologijas, SVV išlieka gyvybiškai svarbios Europos Sąjungos ekonomikai, nes prisideda prie darbo vietų kūrimo bei skurdo mažinimo.

Bendradarbiavimas su ekspertais gali padėti įveikti sudėtingus Pramonės 4.0 integracijos klausimus. Yra daugybė būdų, kaip vykdyti gamybos procesų stebėseną ir tikrinimą, todėl aptarėme įvairius inžinerinius sprendimus, kuriais SVV gali pasinaudoti diegdamos I4.0, tokius kaip daiktų internetas, didžiųjų duomenų analizė, dirbtinis intelektas. Gamybos stebėjimas realiuoju laiku įvardijamas kaip SVV transformuojanti priemonė, teikianti tokią naudą, kaip didesnis veiklos efektyvumas, kokybės valdymas ir išteklių optimizavimas. Skaitmeninių dvynių technologijos, įmonių išteklių planavimo, gamybos vykdymo sistemų diegimas gamyboje yra labai svarbus, tačiau, norint sėkmingai jas pritaikyti, būtina atsižvelgti į žmogiškąjį veiksnį jas integruojant. Tačiau pabrėžiama, kad sklandų šių technologijų diegimą gali stabdyti žinių ir finansinių išteklių trūkumas.

Šiomis sistemomis siekiama padidinti gamybos procesų efektyvumą. Pagrindiniai veiksniai gali būti pasirenkami įvairiai, atsižvelgiant į konkrečius gamybos įmonės tikslus ir prioritetus. Reguliari procesų stebėsena ir analizė gali padėti gamybos organizacijoms nustatyti tobulintinas sritis, nustatyti veiklos tikslus ir priimti pagrįstus sprendimus, kad optimizuotų savo veiklą ir skatintų nuolatinį tobulėjimą. Naudodamos realiuoju laiku vykdomą stebėseną, modeliavimą, prognozavimo analizę ir nuotolines galimybes, įmonės gali priimti pagrįstus sprendimus, tobulinti produktų kūrimą ir pasiekti ekonomiškai efektyvų ir veiksmingą gamybos planą, kuris yra raktas į sėkmingą veiklą.

Kaip aprašyta, SVV gali būti vadinamos į darbuotojus orientuotomis įmonėmis, todėl šis veiksnys turi būti įtrauktas į visą veiklos stebėseną. Ekspertai ir jų nuomonė yra pagrindinė sprendimų priėmimo priemonė. Tačiau tai turi šalutinį poveikį, pavyzdžiui, galimos klaidos, ilgas reagavimo laikas, asmeninės interpretacijos. Dėl to šio tipo bendrovėms kyla didesnė rizika priimti neteisingus ir laiko požiūriu neefektyvius sprendimus. Taigi, reikalingas sprendimų priėmimo metodas, ir todėl, remdamiesi literatūros apžvalga, sutelkėme dėmesį į ekonomiškai efektyvaus sprendimo, kuris būtų pagrįstas algoritmais ir beveik realaus laiko gamybos stebėjimu, sukūrimą.

6.3. Tyrimo metodologija

6.3.1. Tyrimo apžvalga

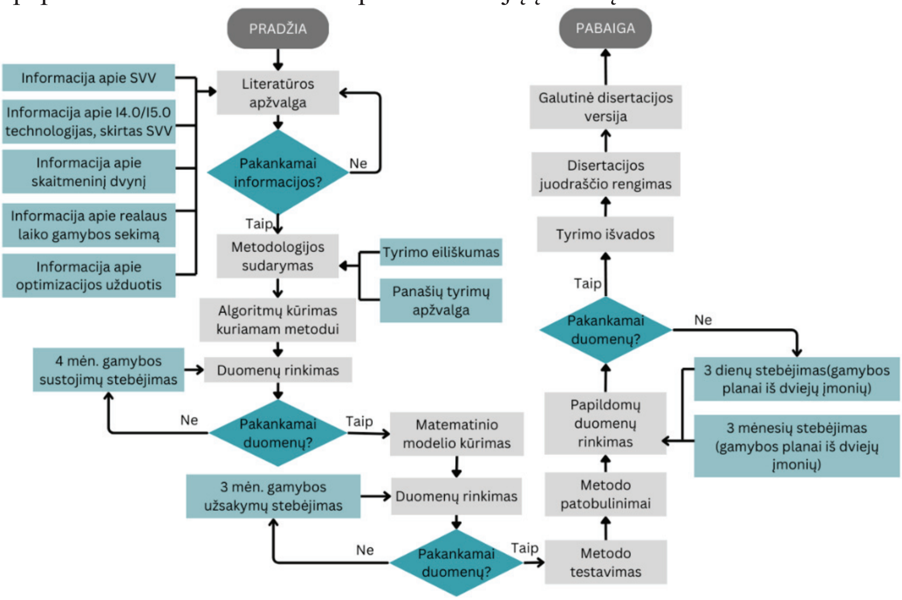
Bendra šio tyrimo metodika pavaizduota 53 paveiksle. Pirmiausia buvo atlikta išsami literatūros apžvalga, siekiant pagrįsti įvairius aspektus. Nors šiuo metu kuriama daugybė gamybos planavimo metodų, nėra dominuojančio planavimo ir analizės metodo. Be to, atsižvelgiant į tai, kad šis tyrimas konkrečiai orientuotas į smulkaus ir vidutinio dydžio įmones, kurios sudaro pagrindinį ekonomikos sektorių, sukurtas metodas turi didelį praktinio taikymo ir vertės kūrimo potencialą.

Siūlomo metodo atveju labai svarbus yra duomenų gavimas, nes metodas remiasi beveik realaus laiko duomenimis. Siekiant nustatyti visas esamas gamybos planavimo spragas ir patvirtinti šio tyrimo naujumą, buvo nuodugniai apžvelgti esami sprendimai šioje srityje.

Tyrimas remiasi skaitmeninių dvynių technologija, apimančia algoritminį gamybos procesų atvaizdavimą, todėl buvo atlikta sisteminė apžvalga ir surinkti atitinkami duomenys. Galutinis šių tyrimų rezultatas – gamybos planavimo optimizavimas.

Norint nustatyti pradinį metodo taikymo objektą, reikėjo surinkti keturių mėnesių stebėjimo duomenis, kad būtų galima susipažinti su veiksniais, lemiančiais gamybos stabdymą. Vėliau, remiantis įgytomis žiniomis, buvo suformuluotas matematinis modelis. Antrasis etapas apėmė trijų mėnesių stebėjimo laikotarpį, apimantį visus per tą laikotarpį apdorotus gamybos užsakymus. Sukurtas metodas buvo išbandytas rankiniu būdu ir patvirtintas naudojant Matlab programinę įrangą. Remiantis šių tyrimų rezultatais buvo įtraukti pataisymai ir papildoma informacija.

Siekiant patikrinti metodo patikimumą ir pritaikomumą, į tyrimo procesą buvo įtraukta papildoma bendrovė ir darbe pateikti dviejų įmonių analizės rezultatai.



53 pav. Metodologijos proceso planas

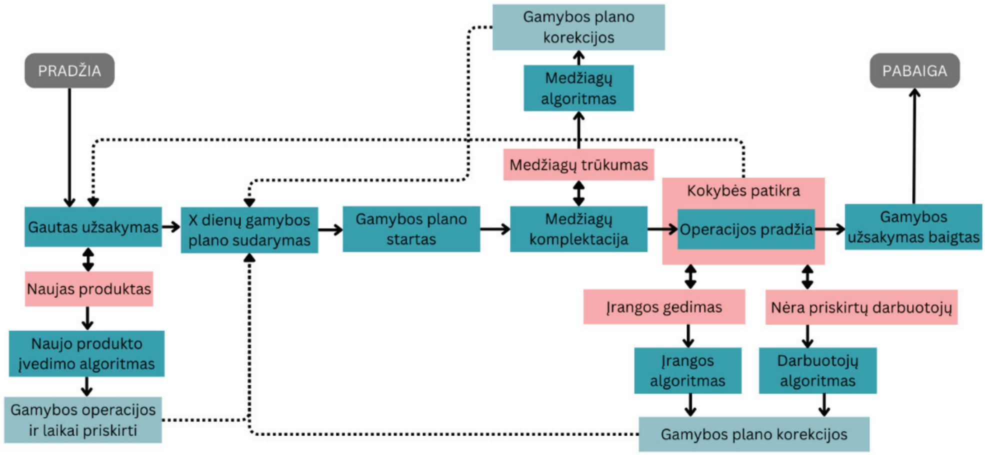
6.3.2. Sprendimų priėmimo metodas

Sprendimų priėmimo metodas veikia nepertraukiamai viso gamybos proceso metu – nuo užsakymo pateikimo į sistemą iki galutinių etapų. Pagrindiniai reikalingi duomenys turėtų būti teikiami naudojant įvairius lengvai įgyvendinamus I4.0 sprendimus – jutiklius, daiktų internetą, PID valdiklius ir kt. Kad būtų lengviau įgyvendinti siūlomą metodą, reikia keleto duomenų masyvų. Esminė informacija apima darbuotojų įgūdžių rinkinius, mašinų parametrus, užduočių prioritetų eiliškumą ir su mašinomis bei darbuotojais susijusias valandines išlaidas. Naudojant šiuos duomenų įvesties duomenis, taikant šį metodą galima priimti pagrįstus sprendimus ir dinamiškai koreguoti gamybos procesus reaguojant į netikėtus sustojimus. Pagrindinis šio metodo tikslas – sumažinti priklausomybę nuo žmogaus priimamų sprendimų ir padidinti veiklos efektyvumą. Sukurtas metodas apima platų sutrikimų, kuriems paprastai reikia ekspertinio sprendimo, spektrą. Sumažinus žmogaus įsikišimą, šis metodas užtikrina racionalesnį ir veiksmingesnį sprendimų priėmimo procesą, taip sumažinama klaidų ir vėlavimų tikimybė. Kadangi šio metodo tikslinė grupė yra SVV, kuriose gamybos dinamika yra neatsiejama, todėl kuriamas metodas turi būti pritaikytas prie greitai kintančių ir nenuspėjamų situacijų. Metodu siekiama padidinti gamybos efektyvumą ir sumažinti neigiamą sutrikimų poveikį pasikliaujant algoritmine analize, o ne vien tik ekspertinėmis žiniomis.

6.3.3. Dinaminis gamybos planavimas

Pagrindinis DGP (dinaminio gamybos planavimo) tikslas – dinamiškai koreguoti gamybos seką beveik realiuoju laiku. Ši metodika specialiai sukurta SVV, kurios nevykdo masinės gamybos ir nenaudoja sudėtingų gamybos planavimo strategijų. Tačiau tokios įmonės paprastai veikia greitai kintančioje aplinkoje, kurioje vyrauja nišinių arba pagal užsakymą atliekamų užsakymų gamyba. Be to, šios įmonės dažnai remiasi darbuotojais, kurie akcentuoja į darbuotojus orientuotą praktiką, o tai dar labiau apsunkina planavimo procesą. Dažniausiai pasitaikančios gamybos problemos ir trikdžiai šiame kontekste yra mašinų gedimai, medžiagų trūkumas, kokybės problemos, naujų produktų įvedimas ir darbuotojų nebuvimas. DGP atsižvelgia į visas šias sritis. Bendrą gamybos ciklą galima pavaizduoti kaip 54 paveiksle.

Raudonai pažymėtos 54 paveikslo dalys sprendžiamos sukurtuoju metodu. Dėl to sutrumpėja bendras gamybos laikas. Galimybė itin greitai gauti apskaičiuotus ir įvertintus sprendimus leidžia įmonėms tęsti gamybą su minimaliais nukrypimais. Taikant šį metodą pastebėta, kad per tą patį gamybos laiką gaunama didesnė gamybos apimtis.



54 pav. Gamybos ciklas

6.3.4. Tirtų gamybos įmonių apžvalga

Šiame darbe dėmesys skiriamas gamybos sektoriaus smulkaus ir vidutinio dydžio įmonėms. Todėl pasirinkta stebima įmonė turėjo atitikti SVV kriterijus. Pažymėtina, kad tyrime noriai dalyvavo dvi skirtingos bendrovės, kurios pateikė svarbią informaciją ir sutiko būti stebimos. Skirtingos bendrovės buvo pasirinktos specialiai, kad būtų galima suprasti metodo apribojimus ir jo universalumą. Abi įmonės aprašytos 19 lentelėje.

19 lentelė. A ir B įmonių pagrindiniai duomenys

	Įmonė A	**Įmonė B**
Tipas	Vidutinio dydžio įmonė	Labai maža įmonė
Darbuotojų skaičius	75	6
Rezultatas	Produktas ir paslaugos	Paslaugos
Sektorius	Baldų gamyba	Automobilių remontas
Operacijų skaičius	13	9
Staklių skaičius	17	14
Pamainos	2	1
Veikia nuo	2005	2018
2022m. pajamos	2500000 Eur	50000 Eur
Operacijos	Rankinis pjovimas juostiniu pjūklu; rankinis pjovimas diskiniu pjūklu; automatinis pjovimas; lankstymas; rankinis šlifavimas; automatinis šlifavimas; tekinimas; gręžimas; perforavimas; suvirinimas; baigiamoji apdaila viso dydžio dažymo kabinoje; apdaila mažoje dažymo kabinoje; pakavimas.	Išardymas; geometrijos atkūrimas; suvirinimas; šlifavimas; dažymas; apdaila; surinkimas; poliravimas; valymas.

6.3.5. Gamybos planavimo kriterijų parinkimas

Kuriamo metodo tikslas yra padidinti gamybos procesų efektyvumą, todėl sukurta optimizavimo užduotis, o tikslo funkcija apima daugiakriterį vertinimą ir yra pagrįsta tiesiniu programavimu. Tam reikalingi skirtingi faktoriai, kuriais būtų galimas situacijos vertinimas. Vienas iš pagrindinių kriterijų yra darbuotojų kompetencijos – ne visi darbuotojai gali vienodai atlikti užduotis, nes turi skirtingą operacijos išmanymo lygį.

Atsižvelgiant į SVV įmonių kontekstą, didelė produkcijos dalis apima unikalius arba vienkartinius užsakymus. Dėl šios priežasties įmonės dažnai neturi iš anksto nustatytų tokių gaminių operacijų laiko, todėl siūlomas metodas negali įvertinti jų gamybos. Siekiant išspręsti šią problemą, siūlomas produktų segmentavimo metodas ir pateikiami algoritmai ir pavyzdžiai, iliustruojantys jo įgyvendinimą.

Be to, gamybos procesuose vienu metu dažnai atliekamos kelios užduotys, todėl jų svarbos nustatymas yra subjektyvus. Vadinasi, pagal siūlomą metodą gamybai reitinguoti būtina įtraukti veiksnius ir jų įverčius. Šie veiksniai parenkami įmonės viduje, ir kiekvienas iš jų turi koeficientus, pabrėžiančius jų svarbą.

6.3.6. Skyriaus išvados ir problemos formulavimas

Stebėjimai parodė, kad SVV gamyba yra dinamiška ir susiduria su keliomis pagrindinėmis problemomis: tai mašinų gedimai, komponentų vėlavimas ir darbuotojų trūkumas. Tyrime dalyvavo dvi skirtingos gamybos įmonės – jose gaminami skirtingi produktai, dirba skirtingas darbuotojų skaičius, vykdoma skirtinga veikla ir pan. Tačiau abiem joms svarbu turėti virtualų asistentą, kuris padėtų valdyti greitai kintančią gamybą. Taigi kuriamas metodas apima dinamišką gamybos aplinką ir perplanuoja gamybos užsakymus efektyviausia seka, kuri sukuriama remiantis optimizavimo uždaviniu. Tai daugiakriteris vertinimas, kai naudojami tokie veiksniai, kaip užduoties svarba, darbuotojų įgūdžių matrica ir kt. Metodui pritaikyti nereikia papildomų išteklių. Patikrinus jį dviejose skirtingose įmonėse, parodytas jo pritaikomumas ir universalumas. Taikant šį metodą, pagrindinis tikslas – sutaupyti bendrą gamybos laiką, sumažinant neefektyvių (pasyvių arba budėjimo) valandų skaičių, ir taip padidinti gamybos pelną. Optimalus išteklių naudojimas taip pat padeda spręsti aplinkosaugos problemas, tinkamas darbuotojų parinkimas užtikrina aukštesnį kokybės lygį ir mažesnį broko kiekį.

6.4. Sprendimų priėmimo modulio ir matematinio modulio kūrimas

6.4.1. DSM DPP algoritmai

Turėdami informaciją apie problemiškiausias gamybos sritis, pagal mūsų metodą sukuriame 3 algoritmus:

- darbuotojų algoritmą, apimantį darbuotojų nebuvimą, jų perskirstymą tarp užduočių (55 pav.);
- mašinų algoritmą, apimantį mašinų gedimus ir gamybos perplanavimą;
- medžiagų algoritmą, kuris randa sprendimą, jei trūksta medžiagų ir negalima laikytis pradinio gamybos plano.

Šie trys algoritmai yra pritaikomi skirtingo pobūdžio gamyboms. Tyrimai buvo atlikti metalo apdirbimo ir automobilių kėbulų remonto įmonėse, ir šios kategorijos buvo universalios abiejose srityse. Šioje disertacijoje daugiausia aprašomas ir pateikiamas darbuotojų algoritmas, nes kiti du algoritmai vadovaujasi ta pačia idėja. Taip buvo nuspręsta remiantis darbuotojų įgūdžių vertinimo naujumu ir tokio kriterijaus nebuvimu perplanuojant gamybą.

55 paveiksle pateikto algoritmo bendrus žingsnius galima apibendrinti taip:

1 žingsnis: Automatinė darbuotojų registracija atliekama naudojant asmenines korteles. Sistema gauna informaciją apie darbuotoją, įskaitant jo vardą, pavardę ir atvykimo bei išvykimo laiko žymas.

2 žingsnis: Jei sistema negauna pranešimų apie darbuotoją, ji automatiškai pereina prie tolesnių etapų, kur reikia naudoti įgūdžių matricą.

3 žingsnis: Algoritmas nagrinėja, ar bet kuris tos pačios pamainos darbuotojas turi daugiau nei 50 % įgūdžių, reikalingų neatvykusio darbuotojo darbui. Iš pradžių šis vertinimas atliekamas tarp toje pačioje pamainoje dirbančių darbuotojų. Tačiau jei pamainoje nerandama tinkamų pakaitalų, sistema išplečia paiešką ir į kitų pamainų darbuotojus, jei tokių yra.

4 žingsnis: Sėkmingas rezultatas pasiekiamas, kai sistema nustato reikiamų įgūdžių turintį darbuotoją, kuris šiuo metu neatlieka jokių priskirtų užduočių. Tokiais atvejais inicijuojamas pakeitimo procesas ir užduotis įvykdoma. Tačiau pasitaiko atvejų, kai kvalifikuotas darbuotojas gali turėti priskirtą užduotį. Tokiais atvejais sistema pradeda vykdyti trijų etapų vertinimo procesą, kad nustatytų, kuriai užduočiai teikiama pirmenybė – šiuo metu darbuotojo atliekamai ar tai, kuri buvo paskirta neatvykusiam darbuotojui. Atliekant šį vertinimą reikia atsižvelgti į įvairius veiksnius, kurie turi būti apibrėžti ir dėl jų susitarta įmonėje. Be to, šių veiksnių vertės ir koeficientai turi būti nustatyti ir patvirtinti visiems užsakymams.

5 žingsnis: Remdamasi trijų etapų vertinimo poreikiu, kiekviena įmonė turi pasirinkti svarbiausius gamybinius veiksnius. Tai gali būti:

- pristatymo terminas;
- šios užduoties (technologinės operacijos) poreikis tolesniems gamybos procesams;
- kiekis;
- klientų reitingavimas;

- papildomi reikalavimai (pvz., tai pavyzdinis didelio kiekio užsakymas; dalys turėtų būti siunčiamos subrangovui ir t. t.).

6 žingsnis: Bendras užduoties svarbos balas apskaičiuojamas taip, kaip parodyta 20 lentelėje. Kiekviena įmonė turi pasirinkti pagrindinius gamybos veiksnius ir įvertinti juos tam tikromis reikšmėmis nuo 0 iki 1, kur arčiau 1 yra svarbiau. Taip pat kiekvienas veiksnys turėtų būti suskirstytas į svarbiausių veiksnių grupes (1 laipsnis), mažiau svarbius 2 laipsnio veiksnius, kurie bus vertinami, jei 1 laipsnio nepakaktų, ir galiausiai 3 laipsnio veiksnius, kurie iš esmės turėtų būti kažkas konkretaus ir unikalaus, kas pakeistų situaciją. Ši atranka kiekvienai gamyklai yra individuali ir turėtų būti aptarta prieš pradedant įgyvendinti metodą. Pavyzdžiui, veiksniai galėtų būti pristatymo laikas, užsakymo kiekis, klientų pozicionavimas, pavyzdžių gamyba ir pan.

20 lentelė. Užduoties svarbos faktorių informacija

Faktorius	**Vertė**	**Laipsnis**
Faktorius 1 (f_1)	V_1	1
Faktorius 2 (f_2)	V_2	1
Faktorius 3 (f_3)	V_3	2
...	...	...
Faktorius n (f_n)	V_n	3

Koeficiento skaičiavimo formulė:

$$v = \sum f_n \cdot V_n, \tag{53}$$

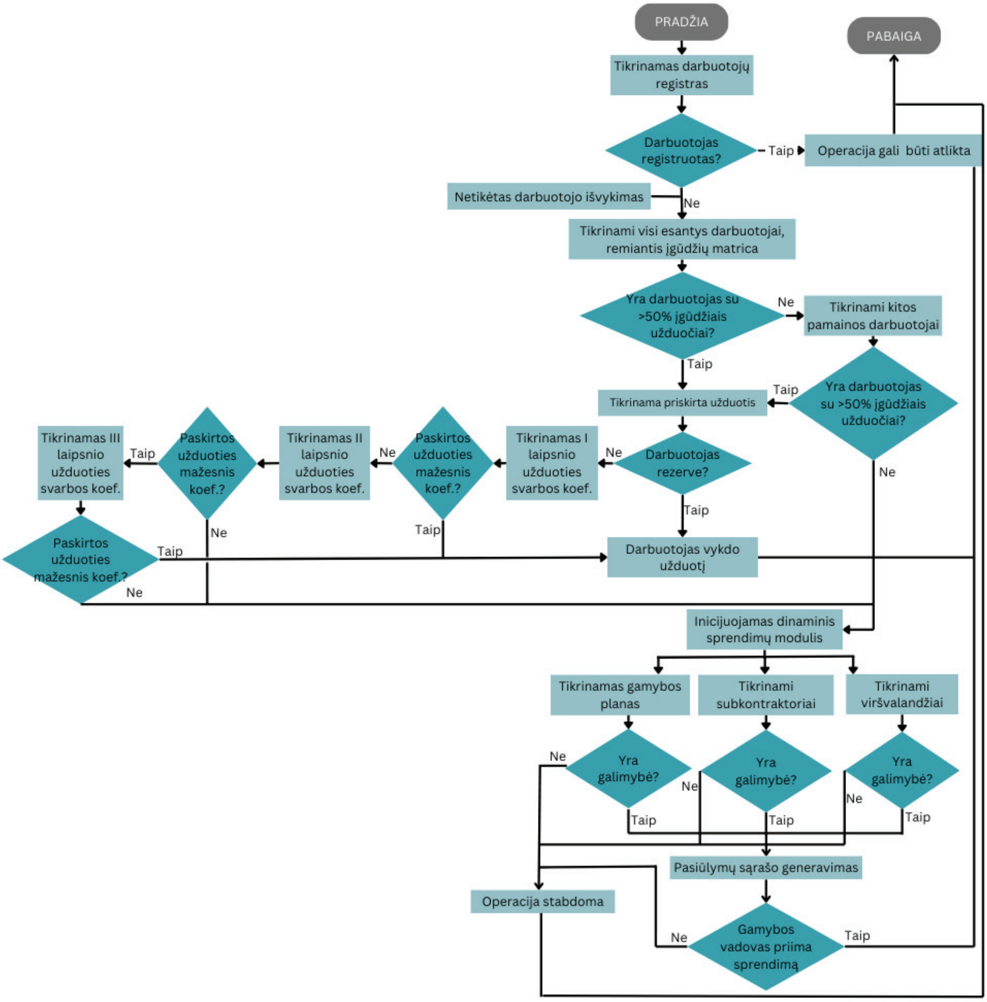
čia: V_n – faktoriaus vertė užduočiai;

f_n – faktoriaus vertė.

7 žingsnis: Tačiau gali susidaryti situacija, kai nėra darbuotojo, kuris galėtų atlikti būtiną gamybos perkonfigūravimą. Tokiais atvejais pradeda veikti dinaminės sprendimų paramos (DSP) modulis. Šis modulis atlieka išsamų papildomų išorinių duomenų įvertinimą ir suformuluoja pasiūlymą. Pavyzdžiui, jei trūksta laisvų darbuotojų reikiamoms užduotims atlikti, modulis nagrinėja galimus gamybos užsakymų pakeitimus, subrangovų prieinamumą ir viršvalandžių galimybes. Norint užtikrinti šio proceso veiksmingumą, įmonei būtina importuoti visus svarbius duomenis, įskaitant kontaktinę informaciją, darbo valandas ir subrangovų parengimo laiką. Tai leidžia sistemai savarankiškai nustatyti, ar yra perspektyvus sprendimas, ar ne.

8 žingsnis: Sistema arba nutraukia darbą, arba randa sprendimą.

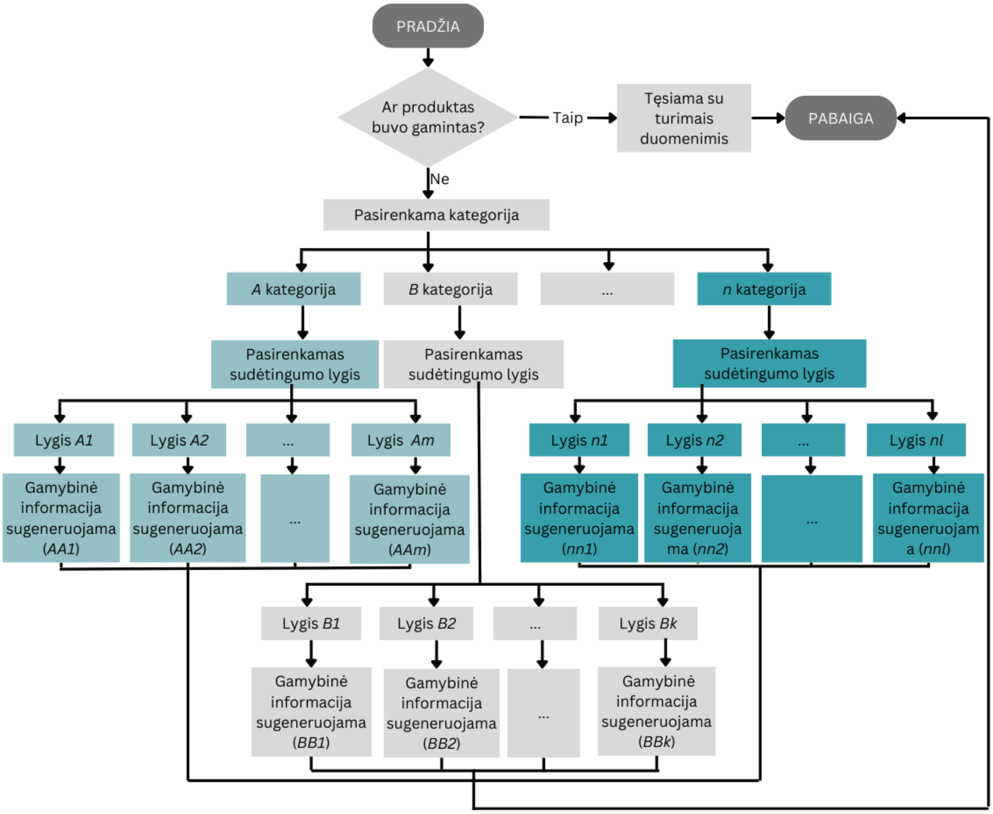
Tokia pati logika taikoma medžiagų ir mašinų algoritmams. Kadangi aprašytų žingsnių galima laikytis taikant ir šiuos algoritmus, vieno iš jų išbandymas suteikia bendrą supratimą apie kitus algoritmus ir jų pagrįstumą.



55 pav. DSM DPP algoritmas darbuotojų kategorijai

Kadangi operacijų laikas ir jų seka yra privaloma informacija šiam metodui inicijuoti, sukurtas naujo produkto įvedimo algoritmas, kuriam susegmentuotos operacijos pagal tam tikrą požymį. 56 paveiksle pateikiamas naujo gaminio algoritmas. Sistema juo vadovaujasi, kai nėra įvesties informacijos apie operacijas.

Kaip parodyta, produktai skirstomi į kategorijas, kurių kiekviena turi savo sudėtingumo lygį. Galutinis rezultatas – pagal sutartas reikšmes bus priskirti operacijų laikas ir procesai.



56 pav. DSM DPP algoritmas naujo produkto segmentavimui

6.4.2. Matematinis modelis

Šiam metodui išbandyti buvo atliktas pateiktų algoritmų matematinis transformavimas, kuris aprašytas šiame poskyryje.

Matematinis modelis pradedamas nuo pradinio dienos plano sukūrimo. Matrica P1 reiškia pradinį dienos planą:

$$P1 = (p1_{ij}), i = \overline{1, k}, \ j = \overline{1, 6}, \qquad (54)$$

čia k – darbuotojų skaičius;

i – eilučių skaičius;

j – stulpelių skaičius.

Reikia kitos matricos M, kurioje pateikiama medžiagų būsena:

$$M = (M_{ij}), i = \overline{1, x}, \ j = \overline{1{,}6}, \qquad (55)$$

čia x – skirtingų medžiagų skaičius;

$M_{i,1}$– medžiagos kiekis sandėlyje;

$M_{i,2}$– reikalingas medžiagos kiekis užsakymui;

$M_{i,3}$– medžiagos kiekis, jau panaudotas atviruose gamybos užsakymuose;

$M_{i,4}$– medžiagos kiekis broko sandėlyje.

Visada tikrinama ir apskaičiuojama, ar užsakymui pakanka medžiagos:

$$M_{i,5} = M_{i,1} - M_{i,3} - M_{i,4}; \quad (56)$$

$$M_{i,6} = \begin{cases} 0, M_{i,5} < M_{i,2} \\ 1, M_{i,5} > M_{i,2} \end{cases}. \quad (57)$$

P1 duomenų masyvo stulpeliai atitinkamai yra:

$$P1_{i,1} = \begin{cases} 0, reikiamos\ įrangos\ nėra \\ 1, įranga\ yra \end{cases}; \quad (58)$$

$$P1_{i,2} = M_{i,6}; \quad (59)$$

$$P1_{i,3} = \begin{cases} 0, nėra\ priskirtos\ užduoties \\ 1, yra\ priskirta\ užduotis \end{cases}. \quad (60)$$

Ketvirtas stulpelis nusako priskirtos užduoties numerį, kurių gali būti *m*:

$$P1_{i,4} = \overline{1, m}. \quad (61)$$

Penktasis stulpelis nusako operacijos numerį, kurių gali būti n. O paskutinis stulpelis nurodo darbuotojų skaičių, kurių gali būti k:

$$P1_{i,5} = \overline{1, n}; \quad (62)$$

$$P1_{i,6} = \overline{1, k}. \quad (63)$$

Pradinis plano patikrinimas apima visų darbuotojų dalyvavimo patvirtinimą, imituojant realias sąlygas. Įvedus šiuos duomenis, sukuriama nauja matrica, žymima S:

$$S = (s_{ij}), i = \overline{1, k},\ j = \overline{1, 4}. \quad (64)$$

Matricos S stulpeliuose esantys elementai gali įgyti konkrečias reikšmes, kaip nurodyta toliau:

$$S_{i,1} = \begin{cases} 0, darbuotojo\ nėra \\ 1, darbuotojas\ yra \end{cases}. \quad (65)$$

Kitas tikrinimo etapas apima nustatymą, ar darbuotojas gali pradėti naują operaciją, o tai reiškia, kad reikia užtikrinti medžiagų, tinkamai veikiančios įrangos ir pradinės užduoties paskyrimą. Šiam vertinimui atlikti naudojami P1 matricos duomenys:

$$S_{i,2} = P1_{i,1} \cdot P1_{i,2} \cdot P1_{i,3} = \begin{cases} 0, darbuotojas\ gali\ dirbti \\ 1, darbuotojas\ negali\ dirbti \end{cases}. \quad (66)$$

Trečiasis matricos S stulpelis rodo, ar suplanuota užduotis bus vykdoma:

$$S_{i,3} = S_{i,1} \cdot S_{i,2} = \begin{cases} 0, užduotis\ nevykdoma \\ 1, užduotis\ vykdoma \end{cases}. \quad (67)$$

Remiantis pirmųjų trijų stulpelių reikšmėmis, užpildomas rezultatų stulpelis:

$$S_{i,4} = S_{i,1}+S_{i,3} = \begin{cases} 0 \\ 1 \\ 2 \end{cases}. \tag{68}$$

Galutinis rezultatas "1" reiškia, kad darbuotojas budi, rezultatas "2" reiškia, kad jokių pakeitimų nereikia, o jei rezultatas lygus "0", reikia atlikti tolesnį vertinimą, kad būtų nustatyta, ar po patikrinimo rezultatas bus "0" (nereikia imtis jokių veiksmų), ar "1" (reikia pakeisti darbuotoją).

Po to sudaroma matrica C, kurios atitinkami elementai jos stulpeliuose gali įgyti konkrečias reikšmes. Stulpelių skaičius priklauso nuo operacijų skaičiaus:

$$C_{i,1} = \overline{1,k}; \tag{69}$$

$$C_{i,2} = S_{i,4}; \tag{70}$$

$$C_{i,j} = \begin{cases} 0 \\ 0,25 \\ 0,5 \\ 1 \end{cases}. \tag{71}$$

Matrica *OW* sukurta užduočiai įvertinti, ir jos stulpeliai atitinkamai turi reikšmes, nurodytas žemiau. Trečias stulpelis nurodo pirmo faktoriaus reikšmę, ketvirtas stulpelis antrojo, penktas stulpelis trečiojo ir taip iki *n* faktoriaus vertės.

$$OW_{i,1} = \overline{1,m}; \tag{72}$$

$$OW_{i,2} = \overline{0,1}; \tag{73}$$

$$OW_{i,3} = \overline{0,1}; \tag{74}$$

$$OW_{i,4} = \overline{0,1}; \tag{75}$$

$$OW_{i,5} = \overline{0,1}; \tag{76}$$

$$OW_{i,n} = \overline{0,1}. \tag{77}$$

Apskaičiuojamos pirmo, antro ir trečio laipsnio užduoties vertinimo koeficientų vertės:

$$OW_{i,n+1} = OW_{i,2} + OW_{i,3}; \tag{78}$$

$$OW_{i,n+2} = OW_{i,4} + OW_{i,5}; \tag{79}$$

$$OW_{i,n+3} = OW_{i,n}. \tag{80}$$

Dabar tikrinama sąlyga, kai *y* žymi neatvykusį darbuotoją, o *i* yra galintis pakeisti darbuotojas:

$$OW_{y,7} > OW_{i,7}. \tag{81}$$

Jei reikalingas tolesnis vertinimas, tikrinama sąlyga:

$$OW_{y,8} > OW_{i,8}. \tag{82}$$

Netenkinant ir šios sąlygos, inicijuojamas DPS modulis.

Šiame skyriuje pateikti esminiai matematiniai pagrindai, reikalingi šiam metodui įgyvendinti Matlab programoje ir tolesniems tyrimams atlikti. Rezultatai sėkmingai patvirtino algoritmo teisingumą sprendžiant darbuotojų neatvykimo į darbą problemą. Rezultatai, gauti atlikus Matlab programos tyrimus, išsamiai aprašyti kitame skyriuje.

6.4.3. Automatizuota gamybos vieta

Šis tyrimas orientuotas į SVV, kurios paprastai vadovaujasi į darbuotojus orientuotos įmonės modeliu. Netgi operacijas, kurioms nereikia specifinių žinių, atlieka darbuotojai. Tokias operacijas gali atlikti dauguma darbuotojų, todėl galimybė prireikus rasti pakaitinį darbuotoją yra labai didelė. Kita vertus, atliekant specifines užduotis, pavyzdžiui, suvirinimo, CNC operacijas, reikalingi įgūdžiai, ir įmonė gali susidurti su problemomis, jei neturi daugiau nė vieno specialisto. Dėl šios priežasties į metodą įtraukta įgūdžių matrica. Tačiau pasitaiko atvejų, kai gamyba naudoja robotus, kobotus arba pusiau automatizuotas darbo vietas. Atsižvelgiant į jų kategoriją ir gebėjimus – stacionarūs ar adaptyvūs, tokios mašinos gali atlikti skirtingas užduotis ir vienais atvejais apimti darbuotoją, o kitais – mašinas. Remiantis tuo, darbuotojų ir mašinų algoritmai būtų paveikti papildomais galimais sprendimais. Reikėtų papildomai patikrinti, ar šis automatinis sprendimas gali pakeisti mašinas, ar darbuotoją. Turint automatinę darbo vietą, kuri galėtų atlikti tas pačias užduotis, kaip ir darbuotojas, įgūdžių matrica taip pat turėtų būti papildyta tokiu automatiniu „darbuotoju“ ir jo įgūdžiais. Tą patį reikėtų padaryti ir su mašinų algoritmu – vertinant dalyvautų naujos „mašinos“.

6.4.4. Optimizavimo užduotis

Atsižvelgiant į gamybos procesą, kiekvieno užsakymo trukmę galima apskaičiuoti pagal konkrečias reikalingas operacijas. Taip galima apskaičiuoti bendrą visų užsakymų vykdymo trukmę, jei jie vykdomi nuosekliai. Šio proceso tikslas – optimizuoti užsakymų planavimą, siekiant užtikrinti, kad būtų įdarbinti visi darbuotojai ir panaudotos visos mašinos, taip pasiekiant optimalų panaudojimo lygį ir sutrumpinant bendrą užsakymų vykdymo laiką, vykdant juos vienu metu.

Laiko minimizavimo funkcija:

$$\min T = \min_{1 \le i \le n} \left(\max_{1 \le i \le n} (tg_i) - \min_{1 \le i \le n} (tp_i) \right); \quad (83)$$

$$tp_i \le t_i \le tg_i; \quad (84)$$

$$i = \overline{1:n}, \quad (85)$$

čia T – bendra visų užsakymų vykdymo trukmė;

t_{pi} – i gamybos užsakymo pradžios laikas;

t_{gi} – i gamybos užsakymo pabaigos laikas;

t_i – i gamybos užsakymo vykdymas;

i – gamybos užsakymo numeris;

n – bendras gamybos užsakymų skaičius.

Tikslas yra maksimizuoti darbuotojo arba mašinos sukuriamą vertę, įvertinant naudą. Sukurtoji vertė turi būti didžiausia pasiekiama ir tam pateikta tikslo funkcija, kai gamyboje nėra automatizuotos gamybinės vietos:

$$\max P_{CF} = \max\left(\sum_{i=1}^{n} value_i - \sum_{i=1}^{n}\left(\sum_{j=1}^{m} tx_{ji}\cdot X_j + \sum_{k=1}^{r} ty_{ki}\cdot Y_k\right)\right), \qquad (86)$$

čia P_{CF}– gamybos pralaidumas;

n – užsakymų skaičius;

m– darbuotojų skaičius;

r– mašinų skaičius;

$value_i$– gamybos užsakymo i vertė, gaunama iš šio užsakymo (suma, kuri lieka eliminavus medžiagas);

tx_{ji} –j darbuotojo darbo laikas atliekant i gamybos užsakymą;

X_j – valandinis j darbuotojo įkainis;

ty_{ki}– k mašinos darbo laikas atliekant i gamybos užsakymą;

Y_k – valandinis k mašinos įkainis;

j – darbuotojo numeris.

Jei įmonė turi automatizuotą gamybinę zoną, funkcija gali būti praplėsta, remiantis 6.4.3 aprašymu. Tuomet funkcija bus tokia:

$$\max P_{CF} = \max\left(\sum_{i=1}^{n} value_i - \sum_{i=1}^{n}\left(\sum_{j=1}^{m} tx_{ji}\cdot X_j + \sum_{k=1}^{r} ty_{ki}\cdot Y_k\right) - \delta\sum_{i=1}^{w} tr_i\cdot Z_i\right), \qquad (87)$$

čia w – skaičius darbuotojų ar mašinų, kurios pakeistos automatizuota linija;

tr_i – automatinės linijos i perstatymo laikas;

Z_i – valandinis įkainis automatinės linijos i perstatymo;

$$\delta = \begin{cases} 0, darbuotojas/mašina \rightarrow\ Automatizuotalinija: neinicijuota, \\ 1,\ darbuotojas/mašina \rightarrow\ Automatizuotalinija: inicijuota \end{cases}.$$

Kadangi šis metodas sutrumpina gamybos laiką, nes sumažina sunaudojamų pasyvių gamybos valandų skaičių, įmonė papildomai sutaupo, nes sumažina energijos suvartojimą, kuris aprašytas 6.5 skyriuje. Bendra sutaupyta vertė:

$$S_{ee} = \left(\sum_{k=1}^{r}(\mathrm{T}_k - \sum_{i=1}^{n} ty_{ki})e\right), \qquad (88)$$

čia S_{ee} – sutaupytos energijos piniginė reikšmė;

T_k – visas suplanuotas laikas k mašinai prieš metodo pritaikymą;

e – elektros kaina valandai.

6.4.5. Skyriaus išvados ir problemų formulavimas

Šiame skyriuje pateiktas matematinis modelis. Jis pagrįstas keliais duomenų masyvais:

- medžiagomis M;
- darbuotojų įgūdžiais C;
- pradiniu dienos planu P;

- užduoties svarba OW;
- užduoties atlikimu S.

Matematinis modelis atitinka optimizavimo uždavinį, kuris siekia:

- maksimizuoti įmonės pelną;
- minimizuoti bendrą gamybos laiką.

Kaip papildoma nauda įvertintas energijos taupymas – sutrumpėjęs bendras gamybos laikas virsta sutrumpėjusiomis budėjimo valandomis, kai mašinos eikvoja energiją.

Šiame skyriuje pateiktas naujo gaminio algoritmas. Juo remiantis naujam negaminamam gaminiui galima priskirti darbo laiką ir operacijas, kad jį būtų galima įvertinti sukurtu metodu. Taip pat šiame skyriuje pristatyta situacija, kai galima parinkti automatinę darbo vietą darbuotojui ar mašinai pakeisti. Tuo remiantis buvo modifikuotas optimizavimo uždavinys.

Šis modelis bus išbandytas su realiais duomenimis iš įmonių A ir B. Tyrimai patvirtins metodo naudą. Tai bus pateikta 6.5 skyriuje.

6.5. Sukurto DSM DPP tyrimas įmonėse

6.5.1. Tyrimas įmonėje A

Šis metodas buvo patikrintas rankiniu būdu, naudojant tik pagrindinę informaciją, kad būtų galima suprasti logiką. Gavus teigiamus rezultatus, buvo sukurta ir patikrinta Matlab versija. Šiame skyriuje pateikiami Matlab testavimo rezultatai.

Pasirinktoje tiriamoje bendrovėje vykdoma 13 operacijų.

Darbuotojų įgūdžių matrica, kai yra 13 operacijų ir 18 darbuotojų, bus tokia:

$$C = \begin{pmatrix}
1 & 0,75 & 0,75 & 0,5 & 0 & 0 & 0 & 0 & 0 & 0,5 & 0,75 & 0 & 1 & 1 \\
2 & 0,75 & 0,75 & 0,5 & 1 & 0 & 0 & 0 & 0 & 0,5 & 0,75 & 0 & 1 & 1 \\
3 & 0,75 & 0,75 & 0,5 & 0 & 0 & 0 & 0 & 0 & 0,5 & 0,75 & 1 & 0,75 & 1 \\
4 & 0,5 & 0,5 & 0,25 & 0 & 0 & 0 & 0 & 0 & 0,5 & 0,75 & 0 & 0,75 & 1 \\
5 & 0,5 & 0,5 & 0,25 & 0 & 0 & 0 & 0 & 0 & 0,25 & 0 & 0 & 1 & 1 \\
6 & 0,25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
7 & 0 & 0 & 0 & 0,75 & 0,25 & 0 & 0 & 0,75 & 0 & 0 & 0 & 1 & 1 \\
8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
9 & 0 & 0,25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
10 & 0 & 0 & 0 & 0 & 1 & 0,75 & 0 & 0,5 & 0 & 0 & 0 & 0,75 & 1 \\
11 & 0 & 0,25 & 0 & 0 & 0,75 & 0,5 & 0 & 0,5 & 0 & 0 & 0 & 0,75 & 1 \\
12 & 0,75 & 0,75 & 0,5 & 0 & 0 & 0 & 0 & 0 & 0,5 & 0 & 0 & 1 & 1 \\
13 & 0,75 & 0,75 & 0,5 & 0 & 0 & 0 & 0 & 0 & 0,5 & 0 & 1 & 1 & 1 \\
14 & 0,5 & 0,5 & 0,5 & 0 & 0,75 & 0,5 & 0 & 0 & 0,5 & 0 & 1 & 0,75 & 1 \\
15 & 1 & 1 & 1 & 0 & 0,25 & 0 & 1 & 0,75 & 0,75 & 0 & 0 & 0,75 & 0,75 \\
16 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0,75 \\
17 & 1 & 1 & 1 & 0 & 0,75 & 0,75 & 0 & 0,5 & 1 & 0 & 0 & 1 & 0,75 \\
18 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1
\end{pmatrix}. \quad (89)$$

Antrasis matricos C stulpelis paliekamas tuščias, nes tai yra S matricos stulpelių rezultatas, kuris bus sugeneruotas automatiškai.

Šiam tyrimui iš viso buvo paimti 16 gamybos užsakymų duomenys iš įmonės A. Ši informacija bus naudojama perplanuojant gamybą.

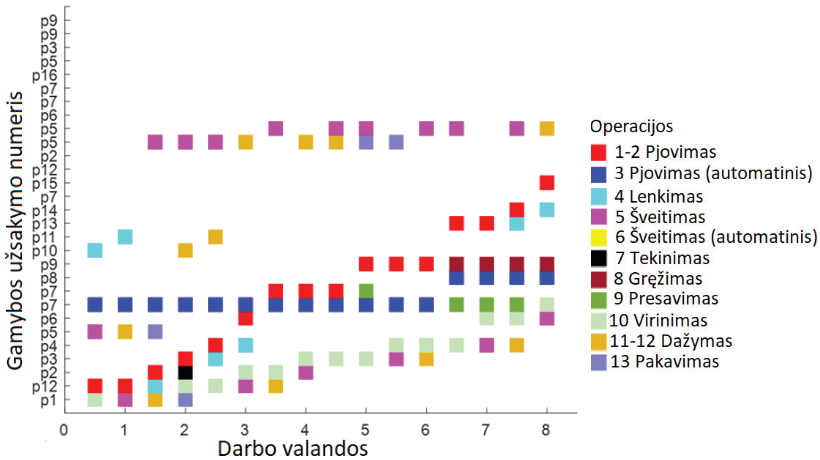
Atliekant šį tyrimą, medžiagų masyvas nebus pildomas, o atsitiktine tvarka parenkamas galutinis rezultatas – medžiagų trūksta ar ne. Taip buvo nutarta dėl mažesnės sistemos apkrovos. Medžiagos paprastai sektų pateiktą duomenų masyvą M, kuriame skirtinga informacija iš sistemos paimama automatiškai.

Kaip aprašyta, įmonė turi nustatyti konkrečius veiksnius, kad prireikus galėtų tinkamai atlikti trijų etapų užduoties svarbos įvertinimą. Todėl 21 lentelėje pateikiami šio konkretaus atvejo tyrimo skaičiai.

Šioje disertacijoje vienos darbo dienos pamainos trukmę padalijome pusvalandžiais, atsižvelgdami į trumpiausią įmanomą užsakymo trukmę. Kad būtų lengviau tai padaryti, sukurta užsakymų matrica, kurioje duomenys suskirstyti į pusės valandos intervalus. Kiekvieną 30 minučių intervalą galima priskirti skirtingoms operacijoms, o operacijų seką galima keisti kas pusvalandį. Kaip parodyta 57 pav., pateikiame pamainos darbo grafiko pavyzdį. Paveikslėlyje skirtingos operacijos pažymėtos spalvomis. Šiai pamainai priskirta dirbti su keliais užsakymais, tačiau iš grafiko matyti, kad yra užsakymų, kurie šiuo metu nevykdomi.

21 lentelė. Pasirinktų užduoties svarbos kriterijų įverčiai

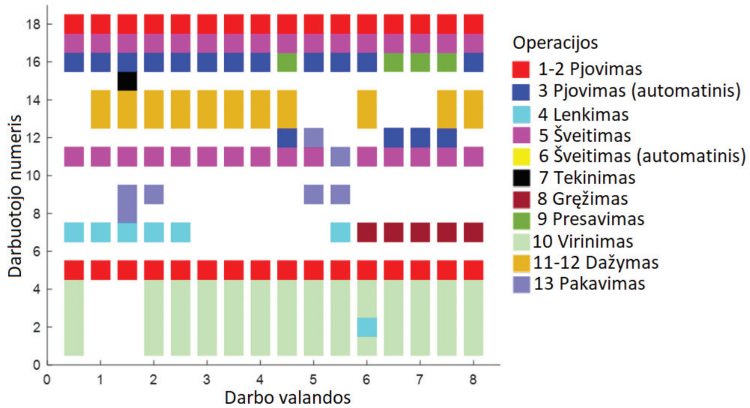
Faktorius	**Vertė**	**Laipsnis**
Pristatymo data (f_1)	0,8	1
Šios užduoties būtinumas kitiems procesams (f_2)	0,9	1
Kiekis (f_3)	0,75	2
Kliento reitingas (f_4)	0,7	2
Papildomi reikalavimai (f_5)	0,2	3



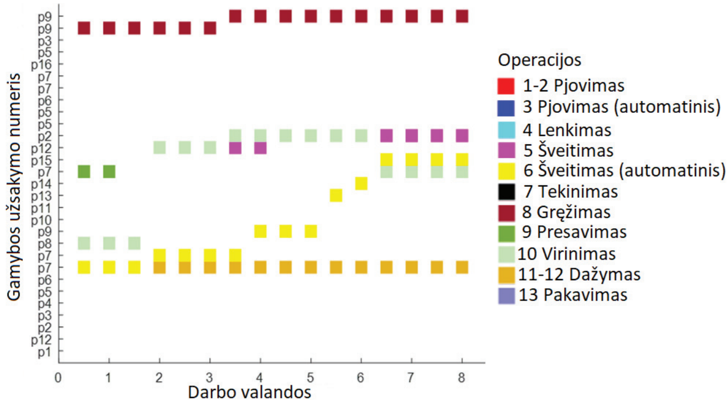
57 pav. Įmonės A gamybos planas pirmai pamainai

Be to, sudaroma matrica, kurioje dokumentuojamos kiekvieno aktyvaus darbuotojo atliktos užduotys. Šioje matricoje pavaizduotos kiekvienam darbuotojui priskirtos konkrečios užduotys ir nurodyti tie darbuotojai, kuriems nepaskirtos užduotys, 58 pav. tai pavaizduota kaip tušti langeliai.

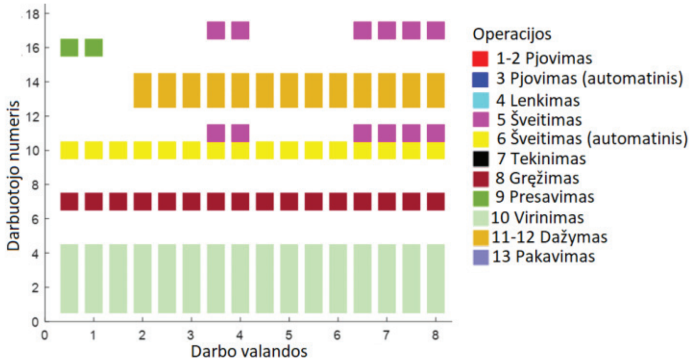
Šioje disertacijoje gilinamasi į realaus gyvenimo scenarijų, analizuojant gamybos planą, sudarytą iš anksčiau minėtų 16 gamybos užsakymų. Iš viso per vieną pamainą dirba 18 darbuotojų, galinčių atlikti 13 skirtingų operacijų. Pradinis vertinimas atliekamas be optimizavimo. Jei gamybos užsakymai apdorojami eilės tvarka pagal jų įvedimo datas, po 8 darbo valandų darbo planas bus kaip 59 paveiksle, o užduočių paskirstymas darbuotojams atsispindės 60 pav. Kaip pavaizduota 59 pav., akivaizdu, kad per antrąsias 8 valandas įvykdoma tik nedaug užsakymų, o tai rodo, kad mašinos ir darbuotojai nepakankamai išnaudojami, kaip parodyta 60 paveiksle. Todėl, siekiant pagerinti bendrą našumą, būtina optimizuoti.



58 pav. Įmonės A darbuotojų užduočių pasiskirstymas pirmai pamainai



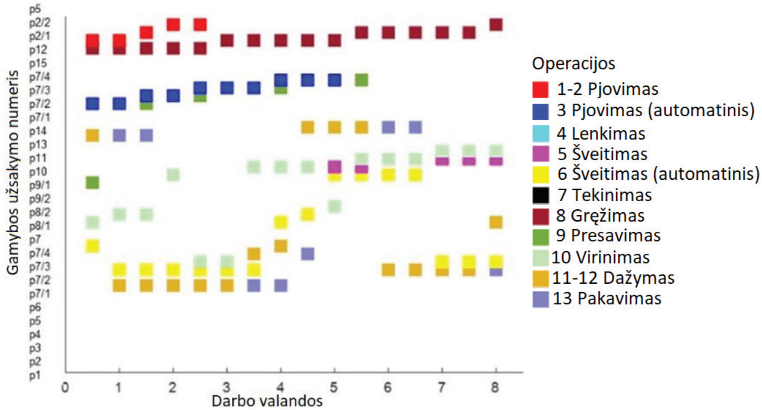
59 pav. Įmonės A gamybos planas antrai pamainai



60 pav. Įmonės A darbuotojų užduočių pasiskirstymas antrai pamainai

Apskaičiuojame kiekvieno užsakymo trukmę (pagal atliekamas operacijas). Randame užsakymų trukmės vidurkį ir tuos užsakymus, kurių trukmė yra didesnė už vidurkį suskaidome į kelis mažesnius, kad jų užsakymo trukmė neviršytų gauto vidurkio (taip darome tam, kad tolygiai pasiskirstytų darbuotojams skirtos operacijos). Tai atlikus, užsakymų skaičius padidėjo iki 29 (nes dideli užsakymai buvo suskaidyti).

61 ir 62 paveiksluose pateikti rezultatai rodo, kaip po pirmųjų 16 valandų aktyvių užsakymų skaičius ir darbuotojų užimtumas paskirstytas, kai užsakymai išskaidyti į mažesnius.

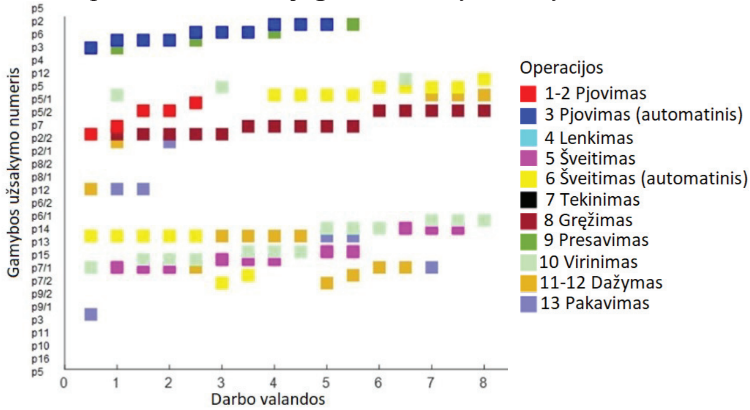


61 pav. Įmonės A gamybos planas trečiai pamainai po užsakymų išskaidymo

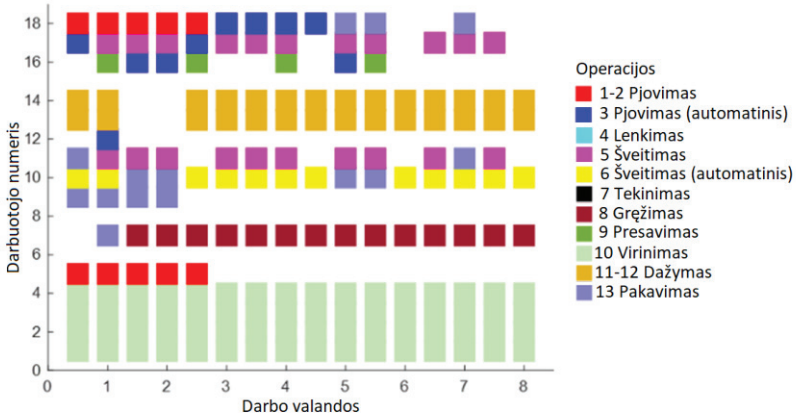
62 pav. Įmonės A darbuotojų užduočių pasiskirstymas trečiai pamainai po užsakymų išskaidymo

Dar sykį atliktas papildomas optimizavimo etapas, kurio metu daugiausia dėmesio skirta gamybos užsakymų prioritetams nustatyti, atsižvelgiant į kelis esminius veiksnius. Konkrečiai buvo nustatyta, kad užsakymų skaičius, mokėjimo tipas, kliento įvertinimas ir užsakymo trukmė yra didžiausią įtaką bendram pelningumui darantys veiksniai.

Šie kriterijai buvo naudojami gamybos užsakymams reitinguoti ir planuoti, siekiant kuo didesnio pelningumo. Remiantis naujausiais rezultatais, gautais atlikus šį optimizavimą, akivaizdu, kad aktyvių gamybos užsakymų skaičius išliko gana pastovus, kaip parodyta 63 pav. Tačiau labai padidėjo darbuotojų atliekamų užduočių įvairovė, todėl padidėjo mašinų išteklių poreikis, kaip parodyta 64 pav. Vis dėlto svarbu pažymėti, kad darbuotojai dirba ne visu pajėgumu, o tai rodo, kad yra galimybių toliau optimizuoti darbo jėgos ir turimų mašinų resursus.

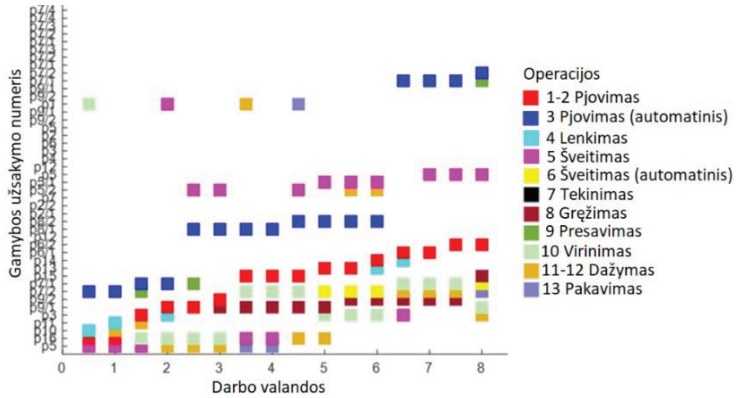


63 pav. Įmonės A gamybos planas trečiai pamainai po užsakymų prioretizavimo

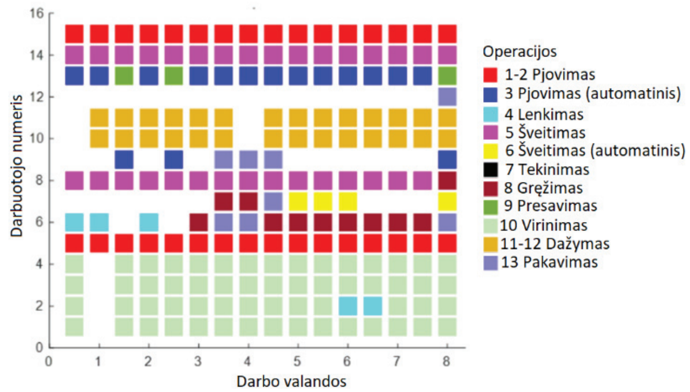


64 pav. Įmonės A darbuotojų užduočių pasiskirstymas trečiai pamainai po užsakymų prioretizavimo

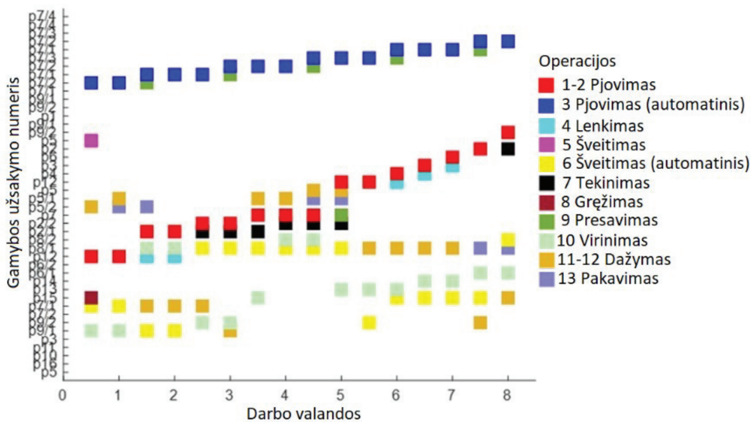
Atlikus analizę matyti, kad yra darbuotojų, kuriems užduočių beveik nėra, tad jų kompetencijos nėra aktualios šiems užsakymams. Taip pradedamas trečias sistemos tyrimas, kai darbuotojai 6, 8 ir 9 yra eliminuojami. 65 ir 66 paveiksluose pavaizduotas pirmosios pamainos darbo planas, o 67 ir 68 paveiksluose – antrosios pamainos darbo planas. Paskutinė pamaina, kuri anksčiau buvo nagrinėjama šiame skyriuje, pateikta 69 ir 70 paveiksluose. Bendras padalytų užsakymų skaičius pasiekė 44.



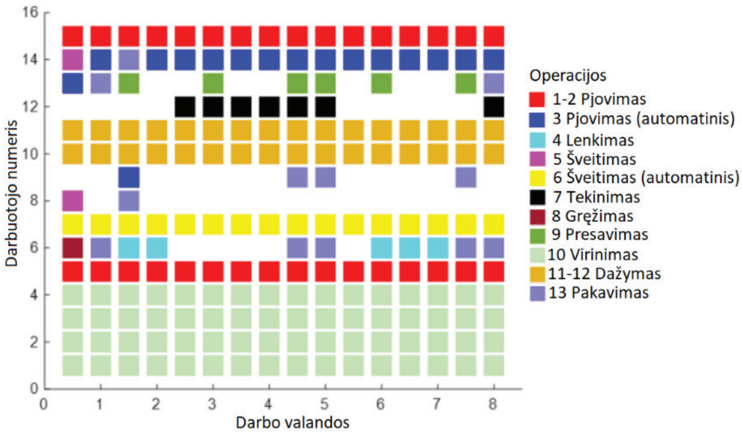
65 pav. Įmonės A gamybos planas pirmai pamainai po darbuotojų skaičiaus sumažinimo



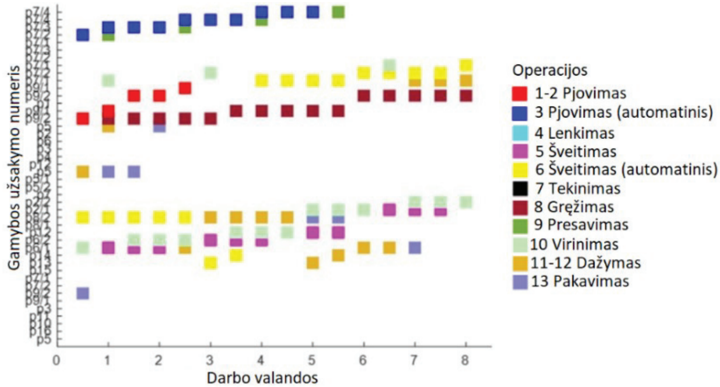
66 pav. Įmonės A darbuotojų užduočių pasiskirstymas pirmai pamainai po darbuotojų skaičiaus sumažinimo



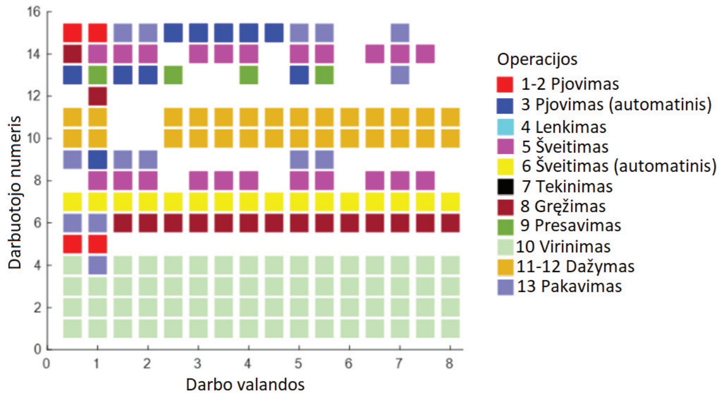
67 pav. Įmonės A gamybos planas antrai pamainai po darbuotojų skaičiaus sumažinimo



68 pav. Įmonės A darbuotojų užduočių paskirstymas antrai pamainai po darbuotojų skaičiaus sumažinimo

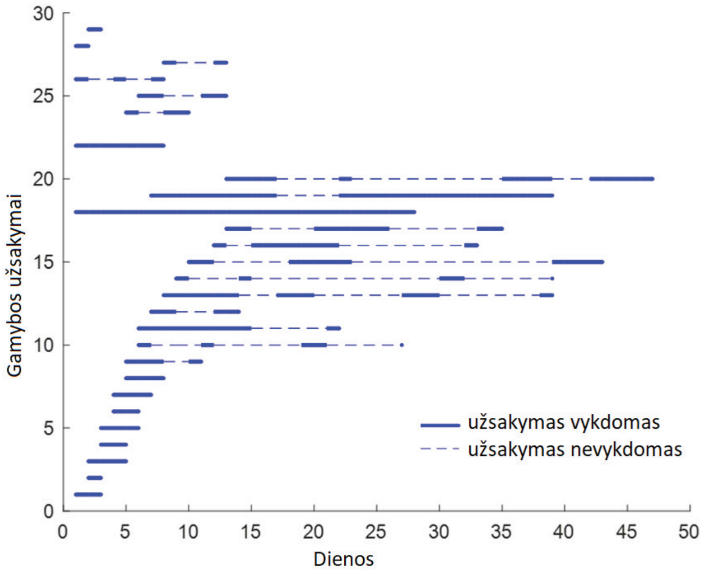


69 pav. Įmonės A gamybos planas trečiai pamainai po darbuotojų skaičiaus sumažinimo

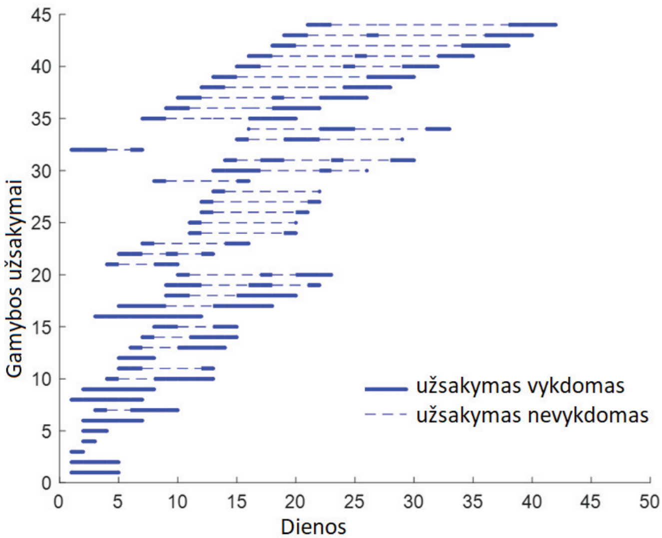


70 pav. Įmonės A darbuotojų užduočių pasiskirstymas trečiai pamainai po darbuotojų skaičiaus sumažinimo

Įgyvendinus aprašytas optimizavimo priemones, sutrumpėjo bendras visų užsakymų gamybos laikas – bendras užsakymų gamybos laikas sutrumpėjo nuo 47 iki 42 valandų. Galima vizualiai palyginti gamybos scenarijus prieš trečiąjį optimizavimo etapą ir po jo, kai pradinis bendras laikas buvo 47 valandos, o vėliau sutaupyta 10% laiko, kaip parodyta atitinkamai 71 ir 72 paveiksluose.

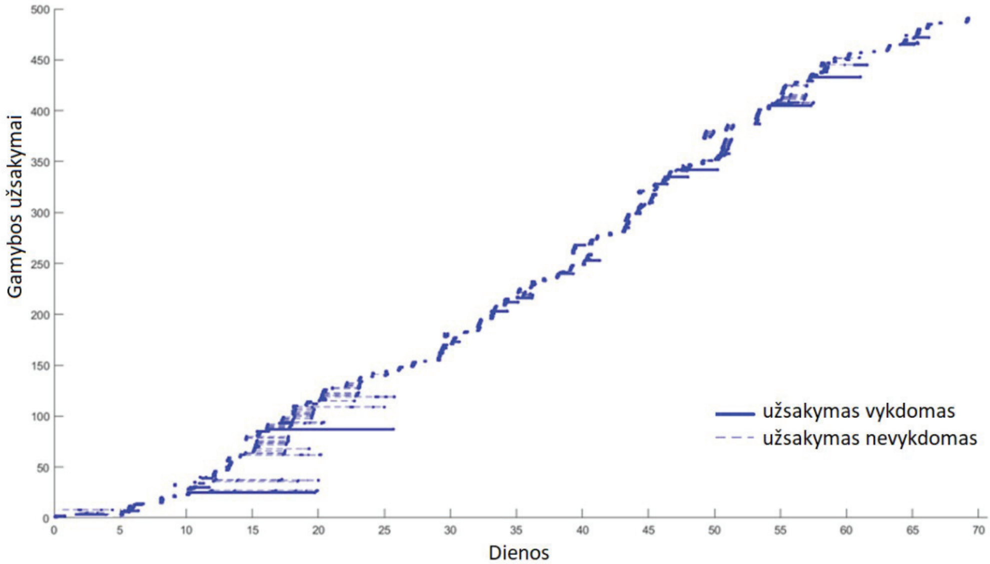


71 pav. Įmonės A gamybos užsakymų pasiskirstymas laike po užsakymų suskaidymo



72 pav. Įmonės A gamybos užsakymų pasiskirstymas laike po darbuotojų skaičiaus mažinimo

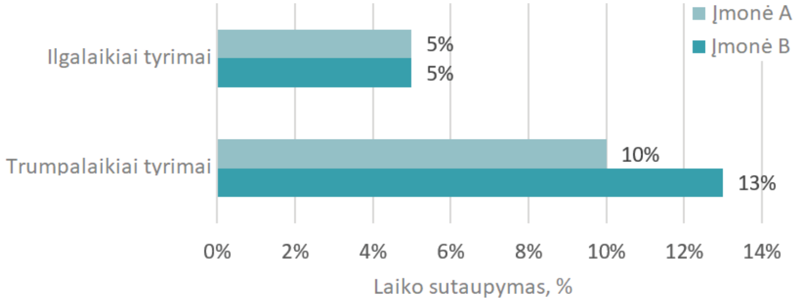
Naudojantis aprašytu metodu, buvo atliktas įmonės A 3 mėnesių (72 darbo dienų) tyrimas, siekiant nustatyti, kiek laiko galima sutaupyti, naudojant metodą. Šio tyrimo metu per sistemą buvo paleistas 491 gamybos užsakymas. Preliminarūs rezultatai rodo, kad metodo įdiegimas leidžia pastebimai sutaupyti laiko pasirinktos Lietuvos įmonės gamybos procesuose. Šis laiko sutaupymas, pasiektas optimizavus procesų pertvarkymą, suteikia galimybę atitinkamai sutaupyti energijos. Stebėtas trijų mėnesių laikotarpis (nuo 2022 m. lapkričio mėn. iki 2023 m. vasario mėn.) rodo reikalingų gamybos dienų sumažėjimą iki 68, taigi apytiksliai 5% mažiau. Gamybos užsakymų pasiskirstymas laike pavaizduotas 73 paveiksle. Tokie tyrimai buvo atlikti ir su įmone B, jie taip pat parodė panašius gamybos procesų efektyvumo padidėjimus.



73 pav. Įmonės A 3 mėnesių gamybos užsakymų pasiskirstymas laike po DSM DPP adaptavimo

6.5.2. Įmonių A ir B rezultatų palyginimas

Rezultatai patvirtino, kad DSM DPP gali būti sėkmingai naudojamas įvairių tipų įmonėse. Abiejose tiriamosiose įmonėse buvo sumažintas reikalingas laikas ir padidintas procesų efektyvumas. Nagrinėtose įmonėse taikant trumpalaikio planavimo metodą buvo pasiekti geresni laiko sutaupymo rezultatai, palyginti su ilgalaikiu planavimu. Trumpalaikis tyrimas įmonėje A buvo atliktas vieną kartą ir sutaupymas siekė 10 %, o įmonėje B po dviejų atskirų tyrimų vidutiniškai sutaupyta 13 % laiko. Taikant ilgalaikį planavimą abiejose bendrovėse sutaupyta apie 5 % laiko. Bendri rezultatai pateikti 74 pav.



74 pav. Trumpalaikių ir ilgalaikių tyrimų rezultatai abiejose įmonėse

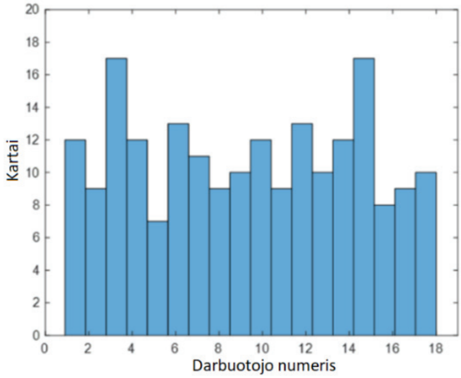
Net jei trumpalaikis planavimas duoda geresnius rezultatus, daugiausia dėmesio reikia skirti ilgalaikio pakartotinio planavimo rezultatams. Kadangi tiriama įmonių grupė paprastai negali tiksliai planuoti trumpuoju laikotarpiu dėl didelės dinamikos, kelių dienų laikotarpio planavimo rezultatai duoda didesnį laiko sutaupymo procentą, pagrįstą ne tokiu tiksliu pradiniu planavimu. Tai buvo patvirtinta abiejose bendrovėse.

6.5.3. Ilgalaikių sprendimų priėmimas

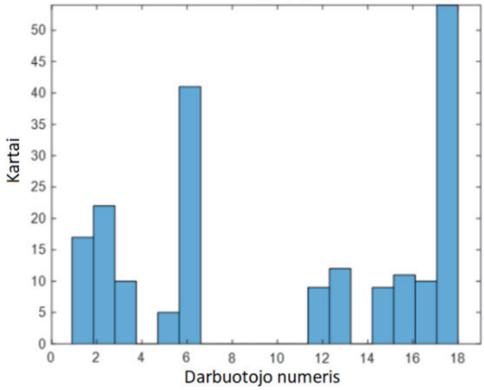
Šie automatiniai gamybos koregavimai ne tik padeda nedelsiant reaguoti į esamas situacijas, bet ir yra galimos rekomendacijos dėl būsimų patobulinimų. Surinkti duomenys gali padėti gauti vertingų įžvalgų, kurios padės parengti būsimus strateginius veiksmus. Tai tampa būsimų tyrimų tema aiškinantis, kaip šis metodas gali ne tik veikti kasdieniniame kontekste, bet ir generuoti pakankamai duomenų veiksmingiems valdymo sprendimams priimti. Surinkti duomenys gali padėti nustatyti sritis, kuriose reikia atnaujinti technologinę įrangą arba parengti darbuotojų įgūdžių ir mokymo planus.

Generuojant atsitiktinius scenarijus programa buvo paleista 200 ciklų. Atsižvelgiant į tai, kad įmonė dirba trimis pamainomis ir programa aktyvuojama kiekvieną kartą atnaujinus įrangą, medžiagas ar darbuotojų statusą, 200 aktyvavimų paprastai įvyktų per maždaug 2 mėnesius. Šio tyrimo rezultatai, atskleidžiantys darbuotojų neatvykimo į darbą dažnumą, pavaizduoti 75 paveiksle.

Remiantis šio tyrimo rezultatais, bendrovės išvadose nurodoma, kad darbuotojai Nr. 3 ir Nr. 15 iš viso neatvyko į darbą 17 iš 200 kartų. Darbuotojas Nr. 3, kuris yra suvirintojas, turi specialių įgūdžių, todėl yra nedaug alternatyvų pakeisti šį darbuotoją. Duomenys, atskleidžiantys, kad šis darbuotojas per du mėnesius neatvyko į darbą beveik 10 % darbo dienų, gali signalizuoti apie strateginių pertvarkymų būtinybę. Be to, siekiant iliustruoti darbuotojų pakeitimo dažnumą, buvo parengti papildomi statistiniai duomenys, pavaizduoti 76 paveiksle.



75 pav. Įmonės A darbuotojų neatvykimo į darbą dažnumas po 200 ciklų



76 pav. Įmonės A darbuotojų pakeitimo dažnumas po 200 ciklų

Iš šių duomenų matyti, kad darbuotojas Nr. 18 dalyvavo maždaug 25% visų atvejų. Šių ciklų generavimo metu yra net septyni darbuotojai, kurie nepakeitė kito darbuotojo nė karto. Būtina ištirti to priežastis ir įvertinti, ar darbuotojų nesugebėjimą pereiti prie kitų užduočių lemia žinių apie šias operacijas trūkumas, o tai gali reikšti, kad reikia mokymų. Tokie mokymai galėtų sumažinti darbuotojo Nr. 18 darbo krūvį, kad pjaustymo operacija (kuri yra pradinis gamybos etapas ir pagrindinė šio darbuotojo užduotis) galėtų vykti be pertraukų. Be to, gali būti, kad šis darbuotojas dengė kitas užduotis, nes jis buvo rezerve dėl įrangos ar medžiagų trūkumo. Tokiais atvejais reikėtų apsvarstyti alternatyvius sprendimus.

Atitinkami tyrimai buvo atlikti ir su įmonės B duomenimis.

6.5.4. Energetinių sąnaudų mažinimas, pritaikius DSM DPP

DSM DPP siekia optimizuoti gamybos procesus, ir kaip papildoma nauda išgaunamas galimas energijos sunaudojimo sumažinimas. Išsamus trijų mėnesių gamybos užsakymų stebėjimo laikotarpis įmonėje A parodė, kad taikant siūlomą metodą galima sumažinti procesų apdorojimo laiką apie 5 %. Remiantis tuo, mažėja energijos naudojimo ir CO_2 suvartojimo pokyčiai, todėl papildomai gaunama finansinė ir ekologinė nauda.

Atlikus tyrimą nustatyta, kad metalo apdirbimo įmonėje A iš viso buvo šeši pagrindiniai mašinų įrenginiai, kurie sunaudoja didžiąją dalį elektros energijos išteklių:

- automatinės vamzdžių pjaustymo staklės (M1);
- CNC tekinimo staklės (M2);
- miltelinio dažymo kamera (M3);
- suvirinimo aparatai (4 vnt.) (M4);
- medienos tekinimo staklės (M5);
- CNC frezavimo staklės (M6).

Buvo būtina nustatyti kiekvieno iš šių įrenginių elektros energijos suvartojimą aktyviuoju ir budėjimo metu. Išsamus šios informacijos suskirstymas pateiktas 22 lentelėje. 23 lentelėje pateikiamas bendras per tiriamąjį laikotarpį suvartotos elektros energijos kiekis.

22 lentelė. Įmonės A pagrindinių įrenginių aktyvi ir budėjimo galia

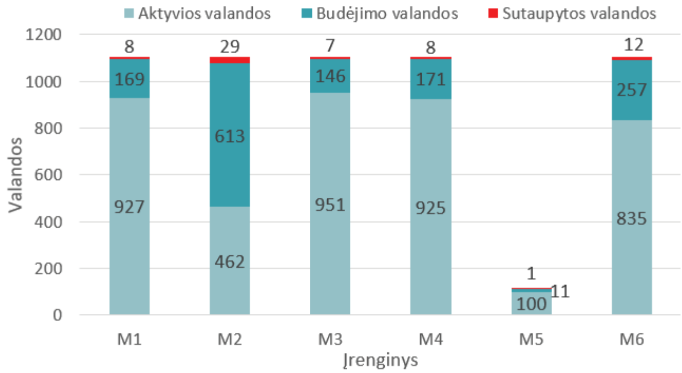
Įrenginio kodas	**Aktyvi galia, kW**	**Budėjimo galia, kW**
M1	4	1.5
M2	7.5	3
M3	15	4
M4	6	1.5
M5	5	1.5
M6	7.5	3

23 lentelė. Elektros suvartojimas įmonėje A per tiriamuosius mėnesius

Metai	**Mėnuo**	**kWh**
2022	Gruodis	14179
2023	Sausis	17866
2023	Vasaris	13424
2023	Kovas	15869

Kaip nurodyta 6.5.1 poskyryje, iš viso per stebimą laikotarpį naudojant sukurtą metodą nuo 2022 m. gruodžio vidurio iki 2023 m. kovo mėn. buvo sutaupytos 4 darbo dienos. Jos gali būti konvertuojamos į 64 darbo valandas, nes gamyba dirbo dviem pamainomis po 8 valandas. Kadangi metodas operacijų laiko nekeičia, šios valandos sutaupytos tik iš budėjimo laiko.

Tai reiškia, kad budėjimo laikas, kuris iš viso buvo 1432 valandos, sutrumpėjo 64 valandomis, t. y. 4,5 %. Sumažėjęs laiko poslinkis pateiktas 77 paveiksle.



77 pav. Aktyvios, budėjimo ir sutaupytos valandos kiekvienam įrengimui, kai pritaikytas DSM DPP

Šie energijos sutaupymai lemia ir išskiriamo CO_2 kiekio sumažėjimą, kas yra būtina prisidedant prie tvaresnės gamybos.

6.5.5. Skyriaus išvados

Kaip matyti iš analizės, metodas buvo taikomas dviejose skirtingose įmonėse – tai rodo jo pritaikomumą ir universalumą. Skirtingos pramonės įmonės, kurios atstovauja skirtingiems sektoriams, lengvai pritaikė siūlomą metodą.

Gamyboje, ypač mažose ir vidutinėse įmonėse, neišvengiamas pakartotinis planavimas. Šio tipo įmonės dirba su didele produktų įvairove, mažais užsakymų kiekiais ir dažniausiai naudojasi tik ekspertų nuomone ir žmogiškosiomis jėgomis. Reaguojant į šią problemą, DSM DPP buvo patikrintas automobilių kėbulų remonto įmonėje, kurioje dirba 6 etatiniai darbuotojai ir atliekamos 9 skirtingos operacijos. Atlikti 3 mėnesių ir 3 dienų trukmės tyrimai. 3 mėnesių tyrimas įmonėje A parodė, kad taikant šį konkretų metodą galima sutaupyti iki 5 % gamybos laiko – nuo 72 iki 68 darbo dienų. Keletas skirtingų tyrimų abejose įmonėse buvo atlikti ir jų suvestinė pateikta 24 lentelėje.

24 lentelė. Atlikti tyrimai įmonėse A ir B

	24 valandų stebėjimas	**3 mėnesių stebėjimas**	**3 dienų planas**	**200 ciklų analizė**
Įmonė A	47 – > 42 val.	72 – > 68 d. d.	-	+
Įmonė B	-	72 – > 68 d. d.	24 – > 20 val. 24 – > 21 val.	+

Šis metodas taip pat parodo duomenų rinkimo svarbą, o, remdamasi kasdien kaupiamais statistiniais duomenimis, įmonė gali turėti rimtą pagrindimą ateities sprendimams. Tai yra papildomas metodo, pagrįsto duomenų rinkimu ir analize, privalumas. Šis metodas suteikia dar vieną papildomą naudą – energijos ir CO_2 sumažinimą. Tyrimų rezultatai parodė, kad įmonėje A dėl elektros energijos suvartojimo sumažinimo išmetamas CO_2 kiekis sumažėjo 27 kg, palyginti su baziniu scenarijumi, kai metodas netaikomas.

6.6. Rekomendacijos

Šis metodas orientuotas į mažas ir vidutinio dydžio įmones. Šis sektorius apima įmones, kurios gamina daug unikalių, nišinių produktų ir neturi masinės gamybos, o kartais dirba net ir su vienetiniais užsakymais. Tokia gamyba yra daugiausiai laiko reikalaujanti, jai trūksta optimizavimo, nes negalima pritaikyti pasikartojančios sekos. Tokias įmones taip pat būtų galima apibūdinti kaip orientuotas į darbuotoją, nes darbo jėga dažniausiai remiasi žmogumi. Nors šis metodas pasižymi pritaikomumu ir tinkamumu įgyvendinti įvairaus dydžio įmonėse, įskaitant didesnes organizacijas, tačiau šio metodo pritaikomumas didelės apimties masinės gamybos įmonėse, kurioms būdingos pažangios technologijos ir skirtingos gamybos stebėjimo sistemos, gali būti ribotas. Nepaisant to, tyrimas patvirtino metodo veiksmingumą gamybos įmonėse, kurios siūlo ne tik galutinius gamybinius produktus, bet ir paslaugas. Atlikus nedidelius patikslinimus, šį metodą galima taikyti įvairiose bendrovėse.

Siūlomą metodą galima laikyti virtualiu gamybos vadovo asistentu, nes jis generuoja atsakymus, kuriuos paprastai pateikia gamybos vadovas po ekspertų vertinimų. Tokios pagalbos būtinybė atliekant šį vaidmenį išryškėjo kritinėse situacijose, kai buvo būtina kuo labiau sumažinti žmonių kontaktą. Remdamasis šiuo metodu, virtualusis asistentas sutaupo didesnės vertės darbo laiko. Taigi ne tik perplanuoja gamybą, kaupia statistiką, bet ir taupo aukštesnės klasės darbuotojų laiką. Taip pat šiuo metodu eliminuojamos žmogiškosios klaidos ir nešališkumas – įgūdžių matrica teikia informaciją apie kiekvienos operacijos įgūdžius, todėl asmuo, neturintis pakankamai įgūdžių, neatliks užduoties.

Taikydamos šį metodą, įmonės, remdamosi gautais rezultatais, gali sudaryti ilgalaikius planus. Reagavimo realiuoju laiku ir pakartotinio planavimo strategijų integravimas su būsimais patobulinimais leidžia įmonėms pasiekti sėkmę ir veiklos efektyvumą. Tradicinėms gamybos planavimo sistemoms dažnai trūksta tinkamų duomenų ir statistikos. Priešingai, šis metodas parodo, kaip praeities veiklos rezultatai gali būti panaudoti vertinant ir optimizuojant ateities planus. Vien tik gamybos optimizavimas realiuoju laiku duoda greitus sprendimus, o ilgalaikių sprendimų įtraukimas gali pastūmėti įmonę į naują veiklos lygį.

IŠVADOS

1. Siekiant užtikrinti veiksmingą ir efektyvų tyrimo tikslų įgyvendinimą, buvo kruopščiai parengta tinkama tyrimo metodika. Buvo pastebėtas metodų pasirinkimo stygius į darbuotojus orientuotoms SVV įmonėms ir sprendimo poreikis dėl labai dinamiškos gamybos aplinkos. Tyrimo metu nustatytos bendros problemos, su kuriomis susiduriama gamybos procesuose, ir, remiantis šiomis išvadomis, suformuluotas metodas.
2. DSM DPP siekiama padidinti gamybos procesų efektyvumą. Pagrindiniai tikslai buvo gamybos laiko sumažinimas ir gamybos resursų išnaudojimo padidinimas, kuriems turi įtakos dinamiškos gamybos problemos – darbuotojų nebuvimas, mašinų gedimai, tiekimo sutrikimai. Šiam tikslui pasiekti buvo pritaikytas sprendimų priėmimo metodas, skirtas dinaminiam gamybos planavimui (DSM DPP), kuris buvo išbandytas dviejose gamybos įmonėse, ir rezultatai parodė teigiamus gamybos perplanavimo rezultatus.
3. DSM DPP metodas buvo sukurtas ir išbandytas Matlab aplinkoje kaip virtualus gamybos asistentas, kuris beveik realiuoju laiku perplanuoja gamybą. Siekiant palengvinti siūlomo metodo įgyvendinimą, buvo sukurti keli duomenų masyvai: darbuotojų įgūdžių rinkiniai, mašinų parametrai, užduočių prioritetų eiliškumas, su mašinomis ir darbuotojais susijusios valandinės išlaidos ir kt. Remiantis gauta informacija, buvo atlikti 24 valandų (3 pamainų) praeities, 3 mėnesių praeities, 3 dienų ateities ir pakartotinio ciklo tyrimai, iš viso 7 unikalūs tyrimai.
4. Siekiant patikrinti siūlomo metodo tinkamumą ir universalumą, buvo atliktas gamybos procesų modeliavimas su realiais tam tikrų gamybos įmonių duomenimis. Buvo stebimos dvi skirtingos įmonės, atstovaujančios skirtingiems dydžiams ir gamybos sritims, siekiant parodyti metodo universalumą. Pirmoji tirta įmonė buvo metalo apdirbimo įmonė, kurios specializacija – baldų komponentų gamyba. Atlikus trijų pamainų tyrimą buvo sutaupyta 10% laiko, o atlikus 3 mėnesių vykdytos gamybos tyrimą – 5%. Antroji bendrovė buvo automobilių kėbulų remonto paslaugų teikėja, teikianti paslaugas individualiems klientams. 3 mėnesių testas parodė, kad sutaupymas siekia 5% laiko, o 3 dienų plano sudarymo testai – 10–15%.

REFERENCES

1. (2021). Policy Learning Platform Brochure. Retrieved from https://www.interregeurope.eu/sites/default/files/inline/Policy_Learning_Platform_brochure.pdf (Accessed 2021 November 22).

2. Friederich, J., Francis, D. P., Lazarova-Molnar, S., & Mohamed, N. (2022). A framework for data-driven digital twins of smart manufacturing systems. *Computers in Industry*, 136. https://doi.org/10.1016/j.compind.2021.103586.

3. European Commission. (2022). Annual Report on European SMEs 2021/22: SMEs and environmental sustainability: SME Performance Review 2021/2022. Retrieved from https://le-europe.eu/publication/2021-2022-annual-report-on-european-smes-june-2022/ (Accessed 2023 October 16).

4. Zheng, H., Lu, Y., Chand, S., Xia, W., Liu, Z., Xu, X., Wang, L., Qin, Z., Bao, J. (2022). Outlook on human-centric manufacturing towards Industry 5.0. *Journal of Manufacturing Systems*, 42, https://doi.org/10.1016/j.jmsy.2022.02.001.

5. Matt, D. T., Modrák, V., Zsifkovits, H. (2017). Industry 4.0 for SMEs. *Springer International Publishing*.

6. Perzylo, A., Rickert, M., Kahl, B., Somani, N., Lehmann, C., Kuss, A., & Danzer, M. (2019). SMErobotics: Smart Robots for Flexible Manufacturing. *IEEE Robotics & Automation Magazine*, 26, https://doi.org/10.1109/MRA.2018.2879747.

7. Ortiz, J. H., Marroquin, W. G., & Cifuentes, L. Z. (2019). Industry 4.0: Current Status and Future Trends. *Journal of Industrial Engineering and Management*, 12(4), https://doi.org/10.5772/intechopen.90396.

8. Ghobakhloo, M., Iranmanesh, M., Vilkas, M., Grybauskas, A., & Amran, A. (2022). Drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs: a systematic review and transformation roadmap. *Journal of Manufacturing Technology Management*, 33, https://doi.org/10.1108/JMTM-12-2021-0505.

9. Brink, T., & Havnen, O. K. (2017). Implementing automation technology in SMEs: A literature review. *Procedia Manufacturing*, 11.

10. Mawson, P., Notarnicola, B., & Philippou, E. (2020). Overcoming Barriers to Industry 4.0 Adoption in SMEs. *Procedia CIRP*, 88.

11. Elhusseiny, H. M., & Crispim, J. (2022). SMEs, Barriers and Opportunities on adopting Industry 4.0: A Review. *Procedia Computer Science*, 196, https://doi.org/10.1016/j.procs.2021.12.086.

12. Salo, J., Majava, J., & Hannula, M. (2021). Exploring Automation Challenges and Readiness in Small and Medium Enterprises: A Multiple Case Study Analysis. *International Journal of Production Research*, 59(3).

13. Yu, F., & Schweisfurth, T. (2020). Industry 4.0 technology implementation in SMEs – A survey in the Danish-German border region. *International Journal of Innovation Studies*, 4(3), https://doi.org/10.1016/j.ijis.2020.05.001.

14. Mittal, S., Khan, M., Romero, D., & Wuest, T. (2018). A Critical Review of Smart Manufacturing & Industry 4.0 Maturity Models: Implications for Small and Medium-sized Enterprises (SMEs). *Journal of Manufacturing Systems*, 49, https://doi.org/10.1016/j.jmsy.2018.10.005.

15. Masood, T., & Sonntag, P. (2020). Industry 4.0: Adoption challenges and benefits for SMEs. *Computers in Industry*, 121, https://doi.org/10.1016/j.compind.2020.103261.

16. Ruiz Zúñiga, E., Syberfeldt, A., Urenda Moris, M. (2017). The Internet of Things, Factory of Things and Industry 4.0 in Manufacturing: Current and Future Implementations. *Advances in Manufacturing Technology XXXI*, https://doi.org/10.3233/978-1-61499-792-4-221.

17. Lin, J., Yu, W., Zhang, N., Yang, X., Zhang, H., & Zhao, W. (2017). A survey on internet of things: Architecture, enabling technologies, security and privacy, and applications. *IEEE Internet Things Journal*, 4, https://doi.org/10.1109/JIOT.2017.2683200.

18. Kumar A. R., Rani, S., Awadh, M. (2022). Exploring the Application Sphere of the Internet of Things in Industry 4.0: A Review, Bibliometric and Content Analysis. *Sensors*, 22, https://doi.org/10.3390/s22114276.

19. Damiani, L., Demartini, M., Giribone, P., Maggiani, M., Revetria, R., & Tonelli, F. (2018). Simulation and digital twin based design of a production line: A case study. *Lecture Notes in Engineering and Computer Science*.

20. Eurostat. (2023). Use of Internet of Things in enterprises. Retrieved from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_Internet_of_Things_in_enterprises (Accessed 2023 June 16).

21. Rauch, E., Matt, D.T. (2021). Status of the Implementation of Industry 4.0 in SMEs and Framework for Smart Manufacturing. *In Matt, D.T., Modrák, V., Zsifkovits, H. (eds) Implementing Industry 4.0 in SMEs*, https://doi.org/10.1007/978-3-030-70516-9_1.

22. Vitkauskaitė, E., Varaniūtė, V., Bouwman, H. (2019). Evaluating SMEs Readiness to Transform to IoT-Based Business Models. *30th European Conference of the International Telecommunications Society (ITS)*.

23. Villarreal Lozano, C., & Vijayan, K. K. (2020). Literature review on Cyber Physical Systems Design. *Procedia Manufacturing*, 45, https://doi.org/10.1016/j.promfg.2020.04.020.

24. Tonelli, F., Demartini, M., Pacella, M., & Lala, R. (2021). Cyber-physical systems (CPS) in supply chain management: From foundations to practical implementation. *Procedia CIRP*, 99, https://doi.org/10.1016/j.procir.2021.03.080.

25. Napoleone, A., Macchi, M., & Pozzetti, A. (2020). A review on the characteristics of cyber-physical systems for the future smart factories. *Journal of Manufacturing Systems*, 54, https://doi.org/10.1016/j.jmsy.2020.01.007.

26. Graessler, I., & Poehler, A. (2019). Human-centric design of cyber-physical production systems. *Procedia CIRP*, 84, https://doi.org/10.1016/j.procir.2019.04.199.

27. Fantini, P., Leitao, P., Barbosa, J., & Taisch, M. (2019). Symbiotic Integration of Human Activities in Cyber-Physical Systems. *IFAC-PapersOnLine*, 52(19), https://doi.org/10.1016/j.ifacol.2019.12.124.

28. Najjari, H., Seitz, M., Trunzer, E., & Vogel-Heuser, B. (2021). Cyber-physical production systems for SMEs-A generic multi-agent based architecture and case study. *2021 IEEE International Conference on Cyber Physical Systems (ICPS)*, https://doi.org/10.1109/ICPS49255.2021.9468232.

29. Saniuk, S., & Grabowska, S. (2021). The Concept of Cyber-Physical Networks of Small and Medium Enterprises under Personalized Manufacturing. *Energies*, 14, https://doi.org/10.3390/en14175273.

30. Rojas, R., & Garcia, M. (2020). Implementation of Industrial Internet of Things and Cyber-Physical Systems in SMEs for Distributed and Service-Oriented Control. *Advances in Industrial Control*, https://doi.org/10.1007/978-3-030-25425-4_3.

31. Shao, G., & Helu, M. (2020). Framework for a digital twin in manufacturing: Scope and requirements. *Manufacturing Letters*, 24, https://doi.org/10.1016/j.mfglet.2020.04.004.

32. Jones, M., Zarzycki, L., Murray, G. (2019). Does Industry 4.0 Pose a Challenge for the SME Machine Builder? A Case Study and Reflection of Readiness for a UK SME. *Precision Assembly in the Digital Age*, 530, https://doi.org/10.1007/978-3-030-05931-6_17.

33. Bag, S., Pretorius, J. H. C., Gupta, S., Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, 163, https://doi.org/10.1016/j.techfore.2020.120420.

34. von der Leyen, U. (2020). State of the Union Address by President von der Leyen at the European Parliament Plenary. Brussels. Retrieved from https://ec.europa.eu/commission/presscorner/detail/en/SPEECH_20_1655 (Accessed 2021 October 15).

35. Digital Europe. (2021). Manufacturing data-sharing as driver for sustainability in Europe. Retrieved from https://www.digitaleurope.org/resources/manufacturing-data-sharing-as-driver-for-sustainability-in-europe/ (Accessed 2022 February 20).

36. Raut, R., Narwane, V., Mangla, S., Yadav, V., Narkhede, B., Luthra, S. (2021). Unlocking causal relations of barriers to big data analytics in manufacturing firms. *Industrial Management & Data Systems*, https://doi.org/10.1108/IMDS-02-2020-0066.

37. Meierhofer, J., Schweiger, L., Lu, J., Züst, S., West, S., Stoll, O., Kiritsis, D. (2021). Digital Twin-Enabled Decision Support Services in Industrial Ecosystems. *Applied Sciences*, 11(23), https://doi.org/10.3390/app112311418.

38. Yasin, A., Pang, T. Y., Cheng, C. T., Miletic, M. (2021). A roadmap to integrate digital twins for small and medium-sized enterprises. *Applied Sciences*, 11(20), https://doi.org/10.3390/app11209479.

39. Minos-Stensrud, M., Haakstad, O.H., Sakseid, O., Westby, B., Alcocer, A. (2018). Towards Automated 3D Reconstruction in SME Factories and Digital Twin Model Generation. *18th International Conference on Control, Automation and Systems (ICCAS)*, https://doi.org/10.23919/ICCAS.2018.8572001.

40. Ritto, T.G., & Rochinha, F.A. (2021). Digital twin, physics-based model, and machine learning applied to damage detection in structures. *Mechanical Systems and Signal Processing*, 155, https://doi.org/10.1016/j.ymssp.2021.107614.

41. Boschert, S., Heinrich, C., & Rosen, R. (2018). Next Generation Digital Twin. *Procedia CIRP*, 72, https://doi.org/10.1016/j.procir.2018.03.258.

42. Kapteyn, M., Knezevic, D., Huynh, D., Tran, M., & Willcox, K. (2022). Data-driven physics-based digital twins via a library of component-based reduced-order models. *International Journal for Numerical Methods in Engineering*, 123(16), https://doi.org/10.1002/nme.6423.

43. Aivaliotis, P., Georgoulias, K., & Chryssolouris, G. (2019). The use of Digital Twin for predictive maintenance in manufacturing. *International Journal of Computer Integrated Manufacturing*, 32(11), https://doi.org/10.1080/0951192X.2019.1686173.

44. Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital Twin: Values, Challenges and Enablers From a Modeling Perspective. *IEEE Access*, 8, https://doi.org/10.1109/ACCESS.2020.2970143.

45. Gaikwad, A., Yavari, R., Montazeri, M., Cole, K., Bian, L., & Rao, P. (2020). Toward the digital twin of additive manufacturing: Integrating thermal simulations, sensing, and analytics to detect process faults. *IISE Transactions*, 52(11), https://doi.org/10.1080/24725854.2019.1701753.

46. Resman, M., Protner, J., Simic, M., Herakovic, N. (2021). A Five-Step Approach to Planning Data-Driven Digital Twins for Discrete Manufacturing Systems. *Applied Sciences*, 11(8), http://dx.doi.org/10.3390/app11083639.

47. Khalaj, O., Jamshidi, M., Hassas, P., Hosseininezhad, M., Mašek, B., Štadler, C., Svoboda, J. (2023). Metaverse and AI Digital Twinning of 42SiCr Steel Alloys. *Mathematics*, 11(1), https://doi.org/10.3390/math11010004.

48. Sarkar, P. (2022). Digital Twin Modeling Using Machine Learning and Constrained Optimization: A Comparative Analysis. Towards Data Science. Retrieved from https://towardsdatascience.com/digital-twin-modeling-using-machine-learning-and-constrained-optimization-401187f2a382 (Accessed 2022 December 8).

49. Wan, Z., Dong, Y., Yu, Z., Lv, H., & Lv, Z. (2021). Semi-Supervised Support Vector Machine for Digital Twins Based Brain Image Fusion. *Frontiers in Neuroscience*, 15, https://doi.org/10.3389/fnins.2021.705323.

50. Lermer, M., & Reich, C. (2019). Creation of Digital Twins by Combining Fuzzy Rules with Artificial Neural Networks, *IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society*, https://doi.org/10.1109/IECON.2019.8926914.

51. Wu, Z., & Li, J. (2021). A Framework of Dynamic Data-Driven Digital Twin for Complex Engineering Products: The Example of Aircraft Engine Health Management, *Procedia Manufacturing*, 55, https://doi.org/10.1016/j.promfg.2021.10.020.

52. Zhang, Y., Li, X., Wang, Y. (2021). Data-driven digital twins for flood prediction: A methodology integrating synchronization analysis and deep learning, *Water*, 13(11), https://doi.org/10.3390/w13111543.

53. Chakraborty, S., Adhikari, S. (2021). Machine learning-based digital twin for dynamical systems with multiple time-scales, *Computers & Structures*, 243, https://doi.org/10.1016/j.compstruc.2020.106410.

54. Liu, D., Du, Y., Chai, W., Lu C., Cong, M. (2022). Digital Twin and Data-Driven Quality Prediction of Complex Die-Casting Manufacturing. *IEEE Transactions on Industrial Informatics*, 18(11), https://doi.org/10.1109/TII.2022.3168309.

55. Biesinger, F., Kras, B., Weyrich, M. (2019). A survey on the necessity for a digital twin of production in the automotive industry. *2019 2nd International Conference on Mechatronics Engineering and Computing Technology (ICMECT)*, https://doi.org/10.1109/ICMECT.2019.8932144.

56. Guise, A., Oliveira, J., Teixeira, S., Silva, G. (2023). Development of tools to support the production planning in a textile company. *Procedia Computer Science*, 219, https://doi.org/10.1016/j.procs.2023.01.364.

57. Li, M., Li, Z., Huang, X., Qu, T. (2021). Blockchain-based digital twin sharing platform for reconfigurable socialized manufacturing resource integration. *International Journal of Production Economics*, 240, https://doi.org/10.1016/j.ijpe.2021.108223.

58. Cimino, C., Negri, E., Fumagalli, L. (2019). Towards the implementation of Digital Twins for industrial robotized processes. *Computers in Industry*, 113, https://doi.org/10.1016/j.compind.2019.103130.

59. Uhlemann, T.H., Lehmann, C., Steinhilper, R. (2017). Digital Twin for Predictive Maintenance: Opportunities and Challenges. *Procedia CIRP*, 61, https://doi.org/10.1016/j.procir.2016.11.152.

60. Graessler, I., Poehler, A. (2017). Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system. *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, https://doi.org/10.1109/IEEM.2017.8289898.

61. Zhang, Y., Xu, H., Huang, J., Xiao, Y. (2023). Research on Multiple Constraints Intelligent Production Line Scheduling Problem Based on Beetle Antennae Search (BAS) Algorithm. *Processes*, 11(3), https://doi.org/10.3390/pr11030904.

62. Ooi, B.-Y., Lee, W.-K., Shubert, M., Ooi, Y.-W., Chin, C.-Y., Woo, W.-H. (2023). A Flexible and Reliable Internet-of-Things Solution for Real-Time Production Tracking with High Performance and Secure Communication. *IEEE Transactions on Industry Applications*, https://doi.org/10.1109/TIA.2023.3255214.

63. Shubhangi, R. B., Devendra, L. B. (2019). Wireless Data Acquisition System. *International Journal of Computer Sciences and Engineering*, 7(1), https://doi.org/10.26438/ijcse/v7i1.690693.

64. da Costa, T.P., Gillespie, J., Cama-Moncunill, X., Ward, S., Condell, J., Ramanathan, R., Murphy, F. (2023). A Systematic Review of Real-Time Monitoring Technologies and Its Potential Application to Reduce Food Loss and Waste: Key Elements of Food Supply Chains and IoT Technologies. *Sustainability*, 15, https://doi.org/10.3390/su15010614.

65. Sneha, G. N., Pooja, M., Subrayamanya, S. (2018). Design of electric sensor using MEMS used for purifying any liquid contents. *International Journal of Engineering Researches and Management Studies*, 5(4).

66. Zhang, Y., Jiang, P., Huang, G., Qu, T., Zhou, G., Hong, J. (2012). RFID-enabled real-time manufacturing information tracking infrastructure for extended enterprises. *Journal of Intelligent Manufacturing*, 23(6), https://doi.org/10.1007/s10845-010-0475-3.

67. Zhang, Y., Liu, S., Liu, Y., Yang, H., Li, M., Huisingh, D., Wang, L. (2018). The 'Internet of Things' enabled real-time scheduling for remanufacturing of automobile engines. *Journal of Cleaner Production*, 185, https://doi.org/10.1016/j.jclepro.2018.02.061.

68. Elias, J.R., Chard, R., Libera, J.A., Foster, I., Chaudhuri, S. (2020). The Manufacturing Data and Machine Learning Platform: Enabling Real-time Monitoring and Control of Scientific Experiments via IoT. *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*, https://doi.org/10.1109/WF-IoT48130.2020.9221078.

69. Hamilton, S. (2021). Real-Time Big Data Analytics, Sustainable Industry 4.0 Wireless Networks, and Internet of Things-based Decision Support Systems in Cyber-Physical Smart Manufacturing. *Economics, Management, and Financial Markets*, 16(2), https://doi.org/10.22381/emfm16220215.

70. Jedermann, R., Praeger, U., Lang, W. (2017). Challenges and opportunities in remote monitoring of perishable products. *Food Packaging and Shelf Life*, 14, https://doi.org/10.1016/j.fpsl.2017.08.004.

71. Tsang, Y.P., Choy, K.L., Wu, C.H., Ho, G.T.S., Lam, H.Y., Tang, V. (2018). An Intelligent Model for Assuring Food Quality in Managing a Multi-Temperature Food Distribution Centre. *Food Control*, 90, https://doi.org/10.1016/j.foodcont.2018.02.032.

72. Hodara, H., Skaljo, E. (2021). From 1G to 5G. *Fiber and Integrated Optics*, 40(2), https://doi.org/10.1080/01468030.2020.1869102.

73. Torres-Sanchez, R., Zafra, M.T.M., Soto-Valles, F., Jiménez-Buendía, M., Toledo-Moreo, A., Artés-Hernández, F. (2019). Design of a Distributed Wireless Sensor Platform for Monitoring and Real-Time Communication of the Environmental Variables during the Supply Chain of Perishable Commodities. *Applied Sciences*, 9, https://doi.org/10.3390/app11136183.

74. Ramírez-Faz, J., Fernández-Ahumada, L.M., Fernández-Ahumada, E., López-Luque, R. (2020). Monitoring of Temperature in Retail Refrigerated Cabinets Applying IoT Over Open-Source Hardware and Software. *Sensors*, 20, https://doi.org/10.3390/s20030846.

75. Klaus, F. (2010). RFID Handbook: Fundamentals and Applications in Contactless Smart Cards, Radio Frequency Identification and Near Field Communication (3rd ed.). John Wiley & Sons Ltd.

76. Shin, S., Eksioglu, B. (2015). An empirical study of RFID productivity in the U.S. retail supply chain. *International Journal of Production Economics*, 163, https://doi.org/10.1016/j.ijpe.2015.02.016.

77. Wang, W., Hu, Z., Zhou, W. (2017). RFID enabled Knowledge-Based precast construction supply chain. *Computer-Aided Civil & Infrastructure Engineering*, 32(4), https://doi.org/10.1111/mice.12254.

78. Huang, Z., Kim, J., Sadri, A., Dowey, S., Dargusch, M. S. (2019). Industry 4.0: Development of a multi-agent system for dynamic value stream mapping in SMEs. *Journal of Manufacturing Systems*, 52(A), https://doi.org/10.1016/j.jmsy.2019.05.001.

79. Nuchjari, I., Chumnumporn, K., Jeenanunta, C., Tunpan, A. (2021). Towards Industry 4.0: digital transformation of traditional safety shoes manufacturer in Thailand with a development of production tracking system. *Engineering Management in Production and Services*, 13(4), https://doi.org/10.2478/emj-2021-0033.

80. Addo-Tenkorang R., Helo, P. (2011). Enterprise Resource Planning (ERP): A Review Literature Report. P*roceedings of the World Congress on Engineering and Computer Science 2011*, 2, https://doi.org/10.13140/2.1.3254.7844.

81. Alaskari, O., Pinedo-Cuenca, R., Ahmad, M.M. (2021). Framework for implementation of Enterprise Resource Planning (ERP) Systems in Small and Medium Enterprises (SMEs): A Case Study. *Procedia Manufacturing*, 55, https://doi.org/10.1016/j.promfg.2021.10.058.

82. Seethamraju, R. (2015). Adoption of Software as a Service (SaaS) Enterprise Resource Planning (ERP) Systems in Small and Medium Sized Enterprises (SMEs). *Information Systems Frontiers*, 17, https://doi.org/10.1007/s10796-014-9506-5.

83. Lutfi, A., Alshira'h, A.F., Alshirah, M.H., Al-Okaily, M., Alqudah, H., Saad, M., Ibrahim, N., Abdelmaksoud, O. (2022). Antecedents and Impacts of Enterprise Resource

Planning System Adoption among Jordanian SMEs. *Sustainability*, 14, https://doi.org/10.3390/su14063508.

84. Hewavitharana, T., Perera, A., Nanayakkara, S. (2019). Prioritizing Enterprise Resource Planning (ERP) Systems for Small and Medium Enterprises. *Journal contribution*, 5(2), https://doi.org/10.6084/m9.figshare.8868389.

85. Ullah, A., Baharun, R. B., Nor, K. M., Siddique, M., Bhatti, M. N. (2018). A Literature Review of ERP Quality Factors. *International Journal of Supply Chain Management*, 7(6), https://doi.org/10.24941/ijscm.v7i6.4202.

86. Kenge, R., Zafar, K. (2020). A Research Study on the ERP System Implementation and Current Trends in ERP. *Shanlax International Journal of Management*, 8(2), https://doi.org/10.34293/management.v8i2.3395.

87. Kozlova, I., Kozlov, A. (2020). Automation of the production planning process as a tool for improving the production activities of a machine-building enterprise. *IOP Conference Series: Materials Science and Engineering*, 869(1).

88. Ali, M., Miller, L. (2021). ERP System Implementation in Large Enterprises - A Systematic Literature Review. *Proceedings of the 23rd International Conference on Enterprise Information Systems*, 2, https://doi.org/10.5220/0010477307760783.

89. Doyle, F., Cosgrove, J. (2019). Steps towards digitization of manufacturing in an SME environment. *Procedia Manufacturing*, 38, https://doi.org/10.1016/j.promfg.2020.01.068.

90. Venkatraman, S., Fahd, K. (2016). Challenges and Success Factors of ERP Systems in Australian SMEs. *Systems*, 4(2), https://doi.org/10.3390/systems4020020.

91. Alshurideh, M. T. (2021). The Impact of Enterprise Resource Planning on Supply Chain Integration: Evidence from Jordanian Nuqul Group Company. *Journal of Supply Chain Management Systems*, 10(1).

92. Khadrouf, O., Chouki, M., Talea, M., Bakali, A. (2020). Influence of SME characteristics on the implementation of ERP. *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, 18(4), https://doi.org/10.12928/TELKOMNIKA.v18i4.13537.

93. Mohd Hafizie, W., Ramayah, T. (2017). Factors affecting cloud-based ERP adoption among SMEs in Penang, Malaysia: A TOE framework. *Journal of Information Systems and Small Business*, 1(1).

94. Oyedele, L. O., Owolabi, H. A., Ajayi, S. O. (2016). Enterprise resource planning adoption in small and medium-sized enterprises: A literature review. *Journal of Manufacturing Technology Management*, 27(4), https://doi.org/10.1108/JMTM-06-2015-0059.

95. Alsharayri, M., Alsharayri, N. (2021). Implementation of cloud ERP in the SME. *Journal of Enterprise Information Management*, 34(2), https://doi.org/10.1108/JEIM-06-2020-0205.

96. Talluri, S. K., & Vasudeva Reddy, A. (2019). Critical success factors of ERP implementation in SMEs. *Journal of Project Management*, 4, https://doi.org/10.5267/j.jpm.2019.6.001.

97. Usman, U. M. Z., Ahmad, M. N., Zakaria, N. H. (2016). Antecedents of cloud ERP adoption in manufacturing industry: Nigerian SMEs context. *6th International Conference*

on Information and Communication Technology for the Muslim World (ICT4M), https://doi.org/10.1109/ICT4M.2016.7814905.

98. Zwolińska, B., Tubis, A. A., Chamier-Gliszczyński, N., Kostrzewski, M. (2020). Personalization of the MES system to the needs of highly variable production. *Sensors*, 20(22), https://doi.org/10.3390/s20226484.

99. Beregi, R., Pedone, G., Háy, B., Váncza, J. (2021). Manufacturing Execution System Integration through the Standardization of a Common Service Model for Cyber-Physical Production Systems. *Applied Sciences*, 11(16), https://doi.org/10.3390/app11167581.

100. Novák, P., Vyskočil, J., Kadera, P. (2019). Plan Executor MES: Manufacturing Execution System Combined with a Planner for Industry 4.0 Production Systems. In Industrial Applications of Holonic and Multi-Agent Systems. HoloMAS 2019. *Lecture Notes in Computer Science*, 11710, Springer, Cham. https://doi.org/10.1007/978-3-030-27878-6_6.

101. Mogensen, R.S., Jacobsen, K.S., Løkkegaard, M., Rasmussen, M.K., Hansen, M.R. (2019). Implementation and Trial Evaluation of a Wireless Manufacturing Execution System for Industry 4.0. *Proceedings of the 2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, Honolulu, HI, USA, https://doi.org/10.1109/VTCFall.2019.8891231.

102. Barni, A., Pietraroia, D., Züst, S., West, S., Stoll, O. (2020). Digital Twin Based Optimization of a Manufacturing Execution System to Handle High Degrees of Customer Specifications. *Journal of Manufacturing and Materials Processing*, 4(4), https://doi.org/10.3390/jmmp4040109.

103. Al-wswasi, M., Ivanov, A., Makatsoris, H. (2018). A survey on smart automated computer-aided process planning (ACAPP) techniques. *Int J Adv Manuf Technol*, 97, https://doi.org/10.1007/s00170-018-1966-1.

104. Soori, M., Asmael, M. (2020). Classification of research and applications of the computer-aided process planning in manufacturing systems. *Independent Journal of Management & Production*, 12(5), https://doi.org/10.14807/ijmp.v12i5.1397.

105. Basinger, K.L., Keough, C.B., Webster, C.E. et al. (2018). Development of a modular computer-aided process planning (CAPP) system for additive-subtractive hybrid manufacturing of pockets, holes, and flat surfaces. *Int J Adv Manuf Technol*, 96, https://doi.org/10.1007/s00170-018-1674-x.

106. Chen, C. S., Sun, Y. T. A. (2017). Intelligent Computer-aided Process Planning of Multi-axis CNC Tapping Machine, *IEEE Access*, 5, https://doi.org/10.1109/ACCESS.2017.2671864.

107. Yunitarini, R., Widiaswanti, E. (2021). Design of Integrated Computer Aided Process Planning and Bill of Material in Industry 4.0 Environment. *E3S Web Conf.*, 328, https://doi.org/10.1051/e3sconf/202132804025.

108. Rojek, I. (2017). Technological process planning by the use of neural networks. *AI EDAM*, 31(1), https://doi.org/10.1017/S0890060416000147.

109. Susac, F., Frumusanu, G., & Afteni, C. (2023). Computer-aided process planning for product launching in manufacturing by the AVAL method. *Acta Technica Napocensis - Series: Applied Mathematics, Mechanics, and Engineering*, 65(4S), https://doi.org/10.2478/atna-2023-0104.

110. Andriani, D., Mardiono, I., Khano, A., Putri, A. (2019). Optimization of Pull-Type Production Process with Computer Aided Process Planning. *Universal Journal of Mechanical Engineering*, 7, https://doi.org/10.13189/ujme.2019.071502.

111. Trstenjak, M., Opetuk, T., Cajner, H., Tosanovic, N. (2020). Process Planning in Industry 4.0—Current State, Potential and Management of Transformation. *Sustainability*, 12(15), https://doi.org/10.3390/su12155878.

112. Zarte, M., Pechmann, A., Nunes, I. L. (2019). Decision support systems for sustainable manufacturing surrounding the product and production life cycle – A literature review. *Journal of Cleaner Production*, 219, https://doi.org/10.1016/j.jclepro.2019.02.092.

113. Antoniadi, A. M., Du, Y., Guendouz, Y., Wei, L., Mazo, C., Becker, B. A., Mooney, C. (2021). Current Challenges and Future Opportunities for XAI in Machine Learning-Based Clinical Decision Support Systems: A Systematic Review. *Applied Sciences*, 11(11), http://dx.doi.org/10.3390/app11115088.

114. Ostaševičius, V. (2022). The State-of-the-Art in the Theoretical and Practical Applications of the Digital Twins Components. In: Digital Twins in Manufacturing. *Springer Series in Advanced Manufacturing*. Springer, Cham, https://doi.org/10.1007/978-3-030-98275-1_1.

115. Guo, Y., Wang, N., Xu, Z., Wu, K. (2020). The internet of things-based decision support system for information processing in intelligent manufacturing using data mining technology. *Mechanical Systems and Signal Processing*, 142, https://doi.org/10.1016/j.ymssp.2020.106630.

116. Zhai, Z., Martínez, J. F., Beltran, V., Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture*, 170, https://doi.org/10.1016/j.compag.2020.105256.

117. Allaoui, H., Guo, Y., Sarkis, J., Hamlog, I. (2019). Decision support for collaboration planning in sustainable supply chains. *Journal of Cleaner Production*, 229, https://doi.org/10.1016/j.jclepro.2019.04.367.

118. Kumar, T. S. (2020). A data mining based marketing decision support system using a hybrid machine learning algorithm. *Journal of Artificial Intelligence and Capsule Networks*, 2(3), https://doi.org/10.36548/jaicn.2020.3.006.

119. Jin, L., Zhou, Z., Li, K., Zhang, G., Liu, Q., Yao, B., Fang, Y. (2022). Applying Evolutionary Multitasking for Process Parameter Optimization in Polymerization Process of Carbon Fiber Production. *Applied Sciences*, 12(18), https://doi.org/10.3390/app12189378.

120. Li, F., Zhang, L., Liao, T. W., Liu, Y. (2019). Multi-objective optimisation of multi-task scheduling in cloud manufacturing. *International Journal of Production Research*, 57(12), https://doi.org/10.1080/00207543.2018.1538579.

121. Gamage, L., De Silva, C. (2012). A source-based dynamic job scheduling approach for flexible manufacturing systems. *International Journal of Manufacturing Research*, 7(3).

122. Liu, W., Liu, B., Sun, D., Li, Y., Ma, G. (2013). Study on multi-task oriented services composition and optimisation with the 'Multi-Composition for Each Task' pattern in cloud manufacturing systems. *International Journal of Computer Integrated Manufacturing*, 26(8), https://doi.org/10.1080/0951192X.2013.766939.

123. Oluyisola, O.E., Bhalla, S., Sgarbossa, F., Strandhagen, J.O. (2022). Designing and developing smart production planning and control systems in the industry 4.0 era: a

methodology and case study. *Journal of Intelligent Manufacturing*, 33, https://doi.org/10.1007/s10845-021-01808-w.

124. Turker, A.K., Aktepe, A., Inal, A.F., Ersoz, O.O., Sena Das, G., Birgoren, B. A. (2019). Decision Support System for Dynamic Job-Shop Scheduling Using Real-Time Data with Simulation. *Mathematics*, 7(3), https://doi.org/10.3390/math7030278.

125. Ito, T., Abd Rahman, M.S., Mohamad, E., Abd Rahman, A.A., Salleh, M.R. (2020). Internet of things and simulation approach for decision support system in lean manufacturing. *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, 14(2), https://doi.org/10.1299/jamdsm.2020jamdsm0027.

126. Zhang, M., Li, C., Shang, Y., Huang, H., Zhu, W., Liu, Y. (2022). A task scheduling model integrating micro-breaks for optimisation of job-cycle time in human-robot collaborative assembly cells. *International Journal of Production Research*, 60(15), https://doi.org/10.1080/00207543.2021.1937746.

127. Jin, L., Zhou, Z., Li, K., Zhang, G., Liu, Q., Yao, B., Fang, Y. (2022). Applying Evolutionary Multitasking for Process Parameter Optimization in Polymerization Process of Carbon Fiber Production. *Applied Sciences*, 12(18), https://doi.org/10.3390/app12189378.

128. Babor, M., Paquet-Durand, O., Kohlus, R., Hammer, B., Nadjm-Tehrani, S. (2023). Modeling and optimization of bakery production scheduling to minimize makespan and oven idle time. *Scientific Reports*, 13, https://doi.org/10.1038/s41598-022-26866-9.

129. Rezig, S., Ezzeddine, W., Turki, S., Rezg, N. (2020). Mathematical Model for Production Plan Optimization—A Case Study of Discrete Event Systems. *Mathematics*, 8(6), https://doi.org/10.3390/math8060955.

130. Statista. (2023). Number of SMEs in Europe by Size. Retrieved from https://www.statista.com/statistics/878412/number-of-smes-in-europe-by-size/ (Accessed 2023 September 8).

131. Official Statistics Portal. (2022). Verslas Lietuvoje 2022: Veikiančios mažos ir vidutinės įmonės. Retrieved from https://osp.stat.gov.lt/en/verslas-lietuvoje-2022/veikiancios-mazos-ir-vidutines-imones (Accessed 2023 January 15).

132. Skėrė, S., Žvironienė, A., Juzėnas, K., Petraitienė, S. (2022). Decision support method for dynamic production planning. *Machines*, 10(11), https://doi.org/10.3390/machines10110994.

133. Skėrė, S., Žvironienė, A., Juzėnas, K., Petraitienė, S. (2022). Optimization Experiment of Production Processes Using a Dynamic Decision Support Method: a Solution to Complex Problems in Industrial Manufacturing for Small and Medium-Sized Enterprises. *Sensors*, 23(9), https://doi.org/10.3390/s23094498.

134. Fani, V., Antomarioni, S., Bandinelli, R., Bevilacqua, M. (2022). Data-driven decision support tool for production planning: a framework combining association rules and simulation. *Computers in Industry*, 144, https://doi.org/10.1016/j.compind.2022.103800.

135. Kardos, C., Laflamme, C., Gallina, V., Sihn, W. (2020). Dynamic scheduling in a job-shop production system with reinforcement learning. *Procedia CIRP*, 97, https://doi.org/10.1016/j.procir.2020.05.210.

136. Maheshwari, P., Kamble, S., Belhadi, A., Mani, V., Abedin, M. (2023). Digital twin-driven real-time planning, monitoring, and controlling in food supply chains. *Technological Forecasting and Social Change*, 195, https://doi.org/10.1016/j.techfore.2023.122799.

137. Cameron, C., Pravin, A. K. (2014). Regression Analysis of Count Data. Cambridge University Press.

138. Skėrė, S., Bastida-Molina, P., Hurtado-Pérez, E., Juzėnas, K. (2023). Energy Consumption Analysis and Efficiency Enhancement in Manufacturing Companies Using Decision Support Method for Dynamic Production Planning (DSM DPP) for Solar PV Integration. *Machines*, 11(10), https://doi.org/10.3390/machines11100939.

139. Nowtricity. (2023). Current emissions in Lithuania. Retrieved from https://www.nowtricity.com/country/lithuania/ (Accessed 2023 June 15).

CURRICULUM VITAE

Simona Skėrė
simona.bukantaite@ktu.lt

Education:

2009 – 2013 Secondary education, Šiauliai Lieporių Gymnasium
2013 – 2017 Bachelor studies of mechanical engineering, Šiauliai University
2017 – 2019 Master studies of mechanical engineering, Šiauliai University

Professional experience:

2018 – 2019 Product development engineer team leader, UAB Baltik vairas
2022 – 2023 Junior Researcher, Kaunas University of Technology
2020 – now STEAM non-formal educator, Šiauliai Creativity Center
2019 – now Chief Development Officer, UAB NMF Metal

Areas of scientific interest:

Production engineering, production efficiency, product development.

Scientific articles on the topic of the dissertation:

1. Skėrė, Simona; Bastida-Molina, Paula; Hurtado-Pérez, Elías; Juzėnas, Kazimieras. Energy Consumption Analysis and Efficiency Enhancement in Manufacturing Companies Using Decision Support Method for Dynamic Production Planning (DSM DPP) for Solar PV Integration // Machines (article in WoS journal), IF: 2.6, Q2. Basel: MDPI. 2023, Vol. 11, art. No. 939, p. 1–21. DOI: 10.3390/machines11100939.
2. Bukantaitė, Simona; Juzėnas, Kazimieras. Evaluation and modelling of production processes affected by unmeasured situations: case study of a metal processing company // Mechanika (article in WoS journal), IF: 0.7, Q4. ISSN: 1392-1207. 2022, Vol. 28, No. 2, p. 152–158. DOI: 10.5755/j02.mech.29285
3. Skėrė, Simona; Žvironienė, Aušra; Juzėnas, Kazimieras; Petraitienė, Stasė. Decision support method for dynamic production planning // Machines (article in WoS journal), IF: 2.6, Q2. Basel : MDPI. ISSN 2075-1702. 2022, Vol. 10, iss. 11, art. No. 994, p. 1–17. DOI: 10.3390/machines10110994
4. Skėrė, Simona, Žvironienė, Aušra; Juzėnas, Kazimieras; Petraitienė, Stasė. Optimization Experiment of Production Processes Using a Dynamic Decision Support Method: a Solution to Complex Problems in Industrial Manufacturing for Small and Medium-Sized Enterprises // Sensors (article in WoS journal), IF: 3.9, Q2. Basel: MDPI. 2023, Vol. 23, iss. 9, art. No. 4498, p. 1–18. DOI: 10.3390/s23094498
5. Bukantaitė, Simona. Factors of smart production processes modernization// HORA 2020: 2nd international congress on human-computer

interaction, optimization and robotic applications (article in WoS conference proceedings). ISBN: 9781728193533, DOI:10.1109/HORA49412.2020.9152832

6. Bukantaitė, Simona; Juzėnas, Kazimieras. Research and modelling of COVID-19 impact on workflow processes: case study of a metal processing company// Mechanika 2021: proceedings of the 25^{th} international scientific conference (abstract in conference proceedings). ISSN: 2783-5677 ; DOI: 10.5755/e01.2783-5677.2021

7. Skėrė, Simona; Žvironienė, Aušra; Juzėnas, Kazimieras; Petraitienė, Stasė. Dynamic Decision Support Method for Dynamic Production Processes: A case study of optimization of Small and Medium-sized Enterprise// Mechanika 2023: proceedings of the 27^{th} international scientific conference (abstract in conference proceedings). DOI: 10.5755/e01.2783-5677.2023

Scientific conferences:

1. National XXVIII workshop of the Lithuanian Association of Computational Mechanics (Factors of the Modernization of Smart Production processes), 15 May 2020, Lithuania
2. International Congress on Human-Computer Interaction, Optimization and Robotic Applications (Factors of the Modernization of Smart Production processes), 26–27 June 2020, Turkey.
3. X^{th} Young researchers' conference (Use of digital twin in the production processes), 16 Sept 2020, Lithuania.
4. National XXIX workshop of the Lithuanian Association of Computational Mechanics (Evaluation of production processes efficiency in metal processing company: case study), 09 Apr 2021, Lithuania.
5. 25^{th} International Conference Mechanika-2021 (Research and Modelling of COVID-19 Impact on Workflow Processes: Case Study of a Metal Processing Company), 21 May 2021, Lithuania.
6. National XXX workshop of the Lithuanian Association of Computational Mechanics (Analysis and creation of the workflow for dynamic production planning), 22 Apr 2022, Lithuania.
7. International Scientific Conference of Young Researchers (Young Researchers for Smart Society) (Analysis and modelling of production planning in a highly dynamic environment), 11 May 2022, Lithuania.
8. 4th International Conference on Robotics Systems and Automation Engineering (Modelling of production processes in dynamic environment), 2022.05.21, Lithuania.
9. National XXXI workshop of the Lithuanian Association of Computational Mechanics (Production Replanning based on Decision Support Method for Dynamic Production Processes: a case study), 11 May 2023, Lithuania.
10. 27^{th} International Conference Mechanika-2023 (Dynamic Decision Support Method for Dynamic Production Processes: A case study of optimization of Small and Medium-sized Enterprise). 26 May 2023, Lithuania

UDK 658.512+005.31](043.3)
SL344. 2024-02-05, 19,25 leidyb. apsk. l. Tiražas 14 egz. Užsakymas 13.
Išleido Kauno technologijos universitetas, K. Donelaičio g. 73, 44249 Kaunas
Spausdino leidyklos „Technologija“ spaustuvė, Studentų g. 54, 51424 Kaunas