DOCTORAL THESIS

Development and Implementation of a Decentralized AI-Driven Control Model for Production Processes

Tõnis Raamets

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Tõnis Raamets

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Detsentraliseeritud tehisintellektipõhise juhtimismudeli väljatöötamine ja rakendamine tootmisprotsessides

TÕNIS RAAMETS

KIRJASTUS

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List of Publications

The list of author's publications, on the basis of which the thesis has been prepared:

I **Raamets, T**., Karjust, K., Hermaste, A., Mahmood, K. (2021). Planning and Acquisition of Real-Time Production Data Through the Virtual Factory in Chemical Industry. *Proceedings of the ASME 2021, 2B: Advanced Manufacturing: International Mechanical Engineering Congress and Exposition IMECE2021, November 1-5, 2021 Virtual (Online), USA.* ASME Digital Collection, V02BT02A017. DOI: 10.1115/IMECE2021-73080.

II Mahmood, K., Karjust, K., **Raamets, T**. (2021). Production Intralogistics Automation Based on 3D Simulation Analysis. Journal of Machine Engineering, 21 (2), 102−115. DOI: 10.36897/jme/137081.

III Golova, J., Mahmood, K., **Raamets, T**. (2021). Simulation based Performance Analysis of Production Intralogistics. IOP Conference Series Materials Science and Engineering, 1140 (1), #012026. DOI: 10.1088/1757-899X/1140/1/012026.

IV **Raamets, T**., Majak, J., Karjust, K., Mahmood, K., Hermaste, A. (2024). Autonomous mobile robots for production logistics: a process optimization model modification. Proceedings of the Estonian Academy of Sciences, 73 (2), 134−141. DOI: 10.3176/proc.2024.2.06.

V Moor, M, Pakkanen, J, **Raamets, T**, Mahmood, K, Riives, J. (2024). Industrial Data Analytics in Manufacturing Shop Floor Level. *AIP Conference Proceedings, 2989/1: Modern Materials and Manufacturing 2023, Tallinn, Estonia, 2-4 May 2023.* Ed. Karjust, Kristo, Kübarsepp, Jakob. New York: AIP Publishing, #030006. DOI: 10.1063/5.0189502.

VI **Raamets, T**, Majak, J, Karjust, K, Mahmood, K, Hermaste, A (2024). Development of Process Optimization Model for Autonomous Mobile Robot Used in Production Logistics. *Modern Materials And Manufacturing 2023: Tallinn, Estonia, 2-4 May 2023.* Ed. Karjust, Kristo, Kübarsepp, Jakob. New York: AIP Publishing, #020008. (AIP Conference Proceedings, 2989). DOI: 10.1063/5.0189299.

VII **Raamets, T**., Karjust, K., Hermaste, A., Kelpman, K. (2025). Virtual factory model development for AI-driven optimization in manufacturing. Proceedings of the Estonian Academy of Sciences, 74 (2), 228−233. DOI: 10.3176/proc.2025.2.26.

VIII **Raamets, T**; Karjust, K; Majak, J; Hermaste, A (2025). Implementing an AI-Based Digital Twin Analysis System for Real-Time Decision Support in a Custom-Made Sportswear SME. Applied Sciences, 15, 14, #7952. DOI: 10.3390/app15147952.

Author's Contribution to the Publications

Contribution to the papers in this thesis are:

I Article I: The author proposed the research topic and defined the study's scope. He was responsible for designing the virtual factory layout and the data acquisition framework. The author conducted the simulation experiments and structured the data flow for real-time KPI collection. He also prepared the manuscript and coordinated the submission process.

II Article II: The author conducted the original research and collected the real-world production data used in the study. The input data for the simulation model and the selection of key performance indicators were based entirely on the author's fieldwork and case analysis. Based on this groundwork, the lead author formulated the conceptual framework for the article. The author also reviewed and validated the model outputs, contributing to the critical assessment of the simulation results.

III Article III: The author provided the case study context, collected operational data from the production environment, and contributed to the formulation of relevant performance indicators for simulation-based analysis. He participated in validating the simulation model by comparing its results with actual production scenarios and provided domain-specific insights that informed the interpretation of the results. The author also reviewed the manuscript and ensured consistency with real-world industrial practices.

IV Article IV: The author was the primary contributor to the research design, problem formulation, and development of the modified process optimization model. He carried out experimental simulations and developed optimization logic based on production flow analysis. The author led the implementation of the case study and validated the outcomes through comparative performance metrics. He also wrote the majority of the manuscript and coordinated the collaborative work between co-authors.

V Article V: The author assisted in the collection of real-time production data from industrial equipment during the case study phase. This support contributed to the development of the empirical dataset used for testing the analytics framework developed by the lead author. The author also provided technical input regarding the setup and operation of the data acquisition environment at the partner company.

VI Article VI: The author initiated the research topic and led the development of the optimization model for autonomous mobile robot (AMR) control in production logistics. He was responsible for defining the operational logic, configuring the simulation environment, and performing the performance analysis of different logistics scenarios. The author also prepared the manuscript draft and coordinated contributions from co-authors.

VII Article VII: The author was responsible for developing the concept and architecture of the virtual factory model. He led the integration of AI-based optimization logic into the simulation environment and coordinated the implementation of the digital twin. The author performed the simulation-based experiments, analyzed results in relation to throughput and workstation performance, and authored the main body of the manuscript.

VIII Article VIII: The author designed and conducted the entire case study based on real production data from the apparel manufacturing industry. He developed the digital twin model, carried out clustering analysis of workstation Overall Equipment Effectiveness OEE and throughput time, and led the integration of optimization results into decision support for production planning. The author wrote the manuscript and managed the submission and revision process.

Abbreviations

3D	Three-Dimensional
ACO	Ant Colony Optimization
AGV	Automated Guided Vehicle
AI	Artificial Intelligence
AMR	Autonomous Mobile Robot
BOM	Bill of Materials
COBOTS	Collaborative Robots
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DIMUSA	Digital Manufacturing Support Application
DMAIC	Define, Measure, Analyze, Improve, Control
DT	Digital Twin
ERP	Enterprise Resource Planning
GA	Genetic Algorithm
HMI	Human-Machine Interface
IoT	Internet of Things
JIT	Just In Time
KPI	Key Performance Indicator
MES	Manufacturing Execution System
MR	Mobile Robot
OEE	Overall Equipment Effectiveness
PLC	Programmable Logic Controller
RMS	Reconfigurable Manufacturing System
SME	Small and Medium-Sized Enterprise
TT	Throughput Time
TPM	Total Productive Maintenance
VC	Visual Components
VF	Virtual Factory
WIP	Work in Progress

1 Introduction

Modern manufacturing systems continue to face persistent inefficiencies due to misalignment between production logistics and real-time workstation needs. Although Industry 4.0 has introduced digital tools such as manufacturing execution systems (MES), Internet of Things (IoT) sensors, and digital twins (DT), their industrial use often remains limited to monitoring or offline analysis rather than real-time control. Many factories, therefore, struggle with issues such as delayed material delivery, unstable buffer levels, frequent micro-stoppages, and unpredictable throughput. These challenges were consistently observed across the industrial use cases addressed in this dissertation, including chemical, food, metal, wood, and apparel manufacturing. As companies move toward Industry 5.0, the need for adaptive, autonomous, and human-centric coordination mechanisms becomes even more critical. This context provides the foundation for the decentralized AI-driven control model developed in this research.

The motivation for addressing these challenges also stems from the author's extensive hands-on experience with industrial digitalization projects, where recurring inefficiencies—such as materials and intermediate products failing to reach workstations on time—regularly caused delays and performance bottlenecks [1]. Observing these patterns in practice revealed the gap between available digital technologies and their actual use in production control, emphasizing the need for a more adaptive and intelligent system that can respond to real-time shop-floor conditions. This practical perspective directly inspired the development of a control approach that combines digital optimization methods with real-time performance signals through decentralized, AI-enhanced decision-making.

The integration of intelligent digital control systems into modern manufacturing has become a strategic focus under the Industry 5.0 framework [2]. Unlike Industry 4.0, which mainly emphasizes automation and data sharing, Industry 5.0 prioritizes human-centricity, flexibility, and the use of artificial intelligence (AI) to support both machine and human decision-making [3,4]. One of the primary operational challenges in industrial settings is inefficient coordination between production logistics and real-time shop-floor operations, which often results in workstation downtime, uneven workloads, and reduced throughput [5,6]. These coordination issues are frequently caused by rigid, top-down scheduling systems that fail to accommodate the dynamic nature of actual production environments. To overcome these challenges, lean manufacturing principles—such as waste reduction, flow enhancement, and standardization-provide a core philosophy for identifying and eliminating inefficiencies in logistics and production alignment [7,8].

To effectively address these inefficiencies, it is crucial to understand the complex interactions between logistics scheduling, real-time decision-making, and production system responsiveness. Figure 1 positions this research within the Industry 5.0 landscape by demonstrating how digital twins serve as the real-time data backbone, how decentralized control enables autonomous local decision-making, and how AI-powered reasoning links these elements into an adaptive, responsive production system.

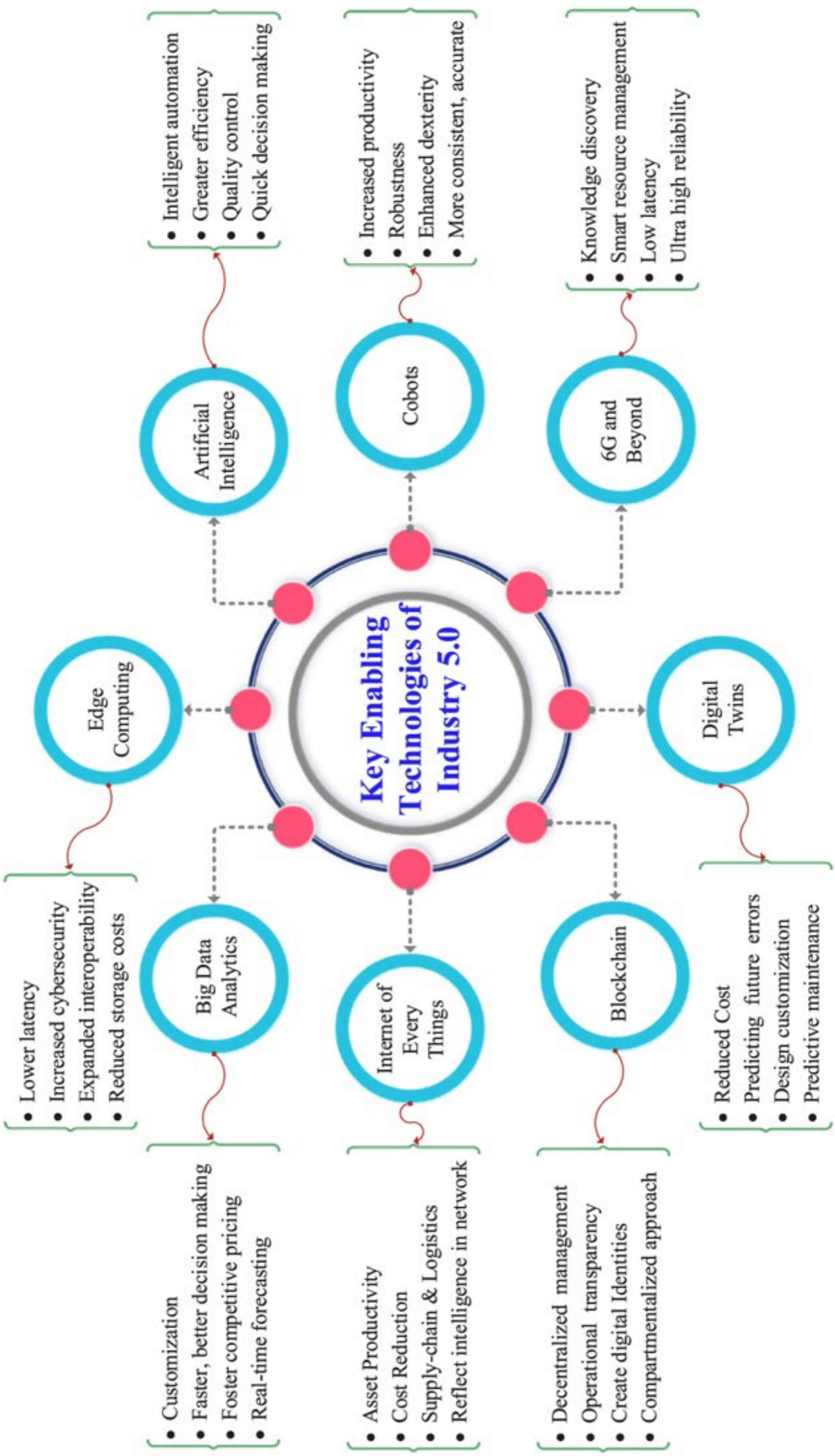


Figure 1. Key enabling technologies of Industry 5.0 [6].

The development process for this research was systematically organized using the Define, Measure, Analyze, Improve, and Control (DMAIC) methodology, a fundamental part of the Lean Six Sigma approach, which provides a structured, data-driven improvement cycle applied throughout this work [9]. Applying DMAIC during the design and validation phases kept a consistent cycle of problem identification, solution development, and empirical feedback. This method ensured that each step, from data collection to system testing, was based on real operational needs and performance analysis [10].

The primary goal of this doctoral research is to develop and implement a decentralized, AI-driven control model for production processes that enables adaptive, autonomous coordination between production logistics and shop-floor operations. The proposed model incorporates digital twin technology, real-time data analytics, and autonomous agent-based decision logic to ensure continuous material flow and balanced workstation performance. By synchronizing logistics operations with the dynamic needs of production, the system improves Overall Equipment Effectiveness (OEE), reduces throughput time, and enhances flexibility and resilience across the manufacturing network [11]. This approach aligns with Industry 5.0's strategic goals by focusing on human-centricity through real-time decision support for operators, coupled with intelligent automation and sustainable productivity in industrial settings.

The main tasks of the thesis are as follows:

- **To design a modular, distributed architecture** in which each production entity (workstation, buffer, or transport unit) functions as an autonomous decision-making agent within the production network.
- **To employ real-time production data and AI algorithms** for analyzing material flow, detecting bottlenecks, and optimizing task allocation through decentralized control logic.
- **To integrate and validate the developed model** in both simulation and industrial environments through digital-twin-based case studies, demonstrating its effectiveness in improving OEE and production flow stability.

The research methodology encompasses digital twin modeling [12], OEE-based performance tracking [13], agent-based and clustering analysis [14], and simulation of intralogistics using autonomous mobile robots (AMRs) [15]. A data-driven approach is applied throughout the work, using real-world production data collected from collaborating industrial companies. The model is validated using both virtual simulations and real-life factory applications. Both Lean principles and the DMAIC cycle were directly integrated into the model design and evaluation criteria. For instance, the system aims to reduce waste by decreasing workstation idle times, preventing overproduction through just-in-time material supply, and standardizing logistics operations using autonomous mobile robots guided by real-time data and AI logic.

The thesis's theoretical novelty lies in the concept of integrating decentralized AI with logistics and production control logic. Unlike traditional MES, which enforces fixed production routing and restricts decision-making to a central authority, the proposed system uses autonomous decentralized control, allowing each node (workstation, buffer, or transport unit) to operate independently with local information, while still ensuring coordinated flow throughout the network system [16]. The practical innovation is demonstrated through five industrial use case studies (chemical, food, metal, wood, apparel), showing that AI-supported autonomous agents can collectively enhance flow stability, decrease idle time, and deliver actionable performance feedback [17]. Early research established the virtual factory and data-acquisition backbone (Publications I and V), providing the foundation for Task 1 – Designing the digital twin model. Mid-phase studies validated AMR coordination and KPI-driven control in simulation (Publications II, III, and VI), directly supporting Task 3 – Simulating with AMRs. Publication IV contributed to Task 2 – Developing AI-based control logic by refining the decentralized optimization model. Late-stage work deployed the DIMUSA platform in SMEs (Publications VII and VIII), completing Task 4 – Validating in production through real industrial implementation. Together, these publications create a coherent progression from architectural development to simulation and industrial validation, fulfilling the thesis research tasks and anchoring the contribution in real operational settings.

The results of this research show that the proposed decentralized model successfully decreased workstation idle time, stabilized overall equipment effectiveness (OEE), and improved responsiveness across all tested cases. The research questions were explored through both simulation and industrial validation, confirming the approach's practical viability. At the same time, the work recognizes limitations related to data quality, legacy system integration, and the gap between simulation and real-world implementation, which provide clear directions for future research.

The results of this research have been shared at international conferences and published in peer-reviewed scientific journals. This thesis is based on eight publications. Together, these publications provide the scientific and empirical foundation for the proposed system.

1.1 Motivation and Significance

The manufacturing industry is undergoing a significant transformation, increasingly influenced by the Industry 5.0 paradigm- a human-centric, sustainable, and resilient approach to industrial development. Unlike its predecessor, Industry 4.0, which focused on automation and connectivity, Industry 5.0 shifts the industrial strategy to prioritize people and the planet in innovation, integrating advanced technologies with societal purpose [18,19]. This represents a strategic transition within the Industry 5.0 framework, aiming to align industrial competitiveness with long-term goals such as ecological balance, inclusive economic growth, and quality employment, thereby redefining technology's role as a means to achieve sustainable societal value. To operationalize this vision, manufacturing systems must evolve from centralized automation toward intelligent, adaptive networks of interconnected agents. Figure 1 illustrates the key enabling technologies that support this transformation, including AI, digital twins, collaborative robots (cobots), and edge computing. These technologies enable production systems to become more autonomous, context-aware, and human-aligned.

However, despite this paradigm shift, recent analysis shows that the European Union is currently trailing behind global competitors, such as the United States and China, in developing and deploying many of these critical technologies. As illustrated in Figure 2, the EU holds comparatively lower leadership shares in fields such as artificial intelligence (AI), cybersecurity, and innovative manufacturing technologies. This technological gap presents a clear call to action: for Europe to secure its industrial future and ensure quality employment, targeted innovation in Industry 5.0 enablers must become a strategic priority [18].

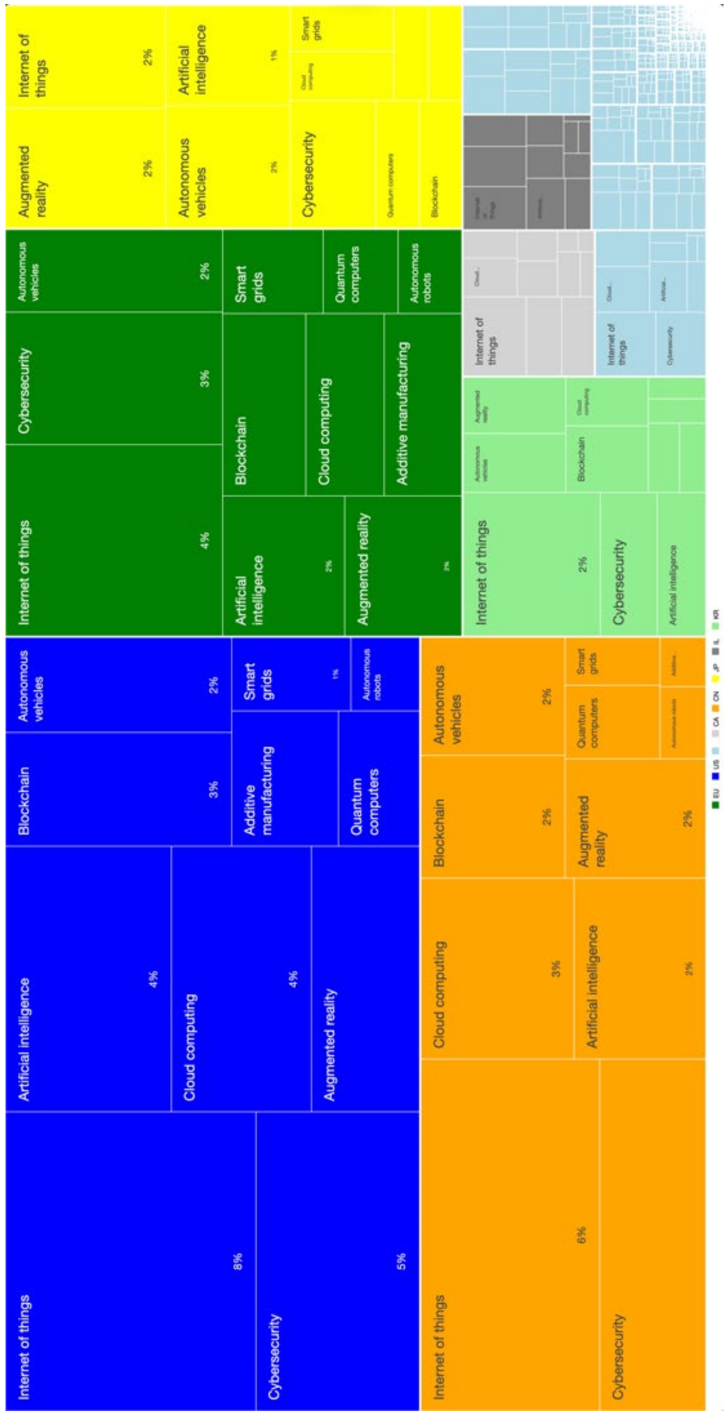


Figure 2.Relative technological leadership in Industry 5.0 domains across global regions. The green segment represents the EU [18].

Despite advances in digitalization, many factories continue to suffer from a persistent bottleneck: the misalignment between logistics flows and the dynamic needs of workstations. Material shortages, transportation delays, and unbalanced workflows often result in idle time and reduced operational efficiency. Traditional centralized control systems frequently lack the responsiveness to manage these real-time fluctuations effectively [20,21]. This challenge highlights the need for more flexible and responsive coordination mechanisms that can maintain stable production flow and minimize the impact of real-time disruptions on throughput and workstation performance. The research draws upon the author's practical experience in industrial digitalization projects, where recurring inefficiencies in material flow and production coordination were observed. The research draws on the author's practical experience in industrial digitalization projects, where ongoing inefficiencies in material flow and production coordination were observed. While individual technological components—such as AMRs, AI-based decision support, real-time OEE monitoring, and digital twins—exist, their isolated use has been insufficient to achieve a stable, adaptive production flow. What remains missing, and what this thesis addresses, is an integrated approach where these components work together within a coherent decentralized control model supported by real-time digital twins, Industry 5.0 principles, and the structured DMAIC improvement cycle.

The proposed approach is especially relevant today as manufacturers look for solutions that go beyond basic automation. It enables systems to adapt in real time, operate autonomously, and improve sustainability and resilience. By treating each production component—workstations, buffers, and transport units—as an autonomous decision-making agent connected through a digital twin and guided by OEE-based feedback, the model supports a flexible and resilient production environment aligned with the main goals of Industry 5.0.

1.2 Research Objectives and Questions

The main goal of this doctoral research is to develop and implement a decentralized, AI-driven control model for production processes that enables adaptive, autonomous coordination between production logistics and shop-floor operations. The proposed system combines digital twin technology, real-time performance data, and AI to ensure continuous material flow and balanced workstation performance. By synchronizing inbound and outbound logistics with evolving production needs, the model aims to enhance throughput, improve OEE, and increase system-wide flexibility and resilience in modern manufacturing environments. This overarching goal aligns with the vision of Industry 5.0, which integrates intelligent automation with human-centricity, sustainability, and adaptive decision-making.

Based on this research aim, the following research questions are formulated:

- **RQ1:** How can a decentralized, AI-driven control model improve the coordination between production logistics and shop floor operations in dynamic manufacturing environments?
- **RQ2:** What impact does such a model have on workstation efficiency, OEE, and overall throughput time?
- **RQ3:** How can real-time data from digital twins be used to assign logistics tasks to a mobile robot dynamically?

In support of validation and performance measurement, a quantitative research question is also introduced:

- **RQ4 (quantitative):** To what extent can the proposed system reduce workstation idle time (%) and improve average throughput time (min) compared to baseline logistics coordination?

To address these questions, the thesis defines the following research tasks:

- **Task 1 – Design a digital twin model** of a production system with modular and real-time data interfaces.
- **Task 2 – Develop AI-based decentralized control logic** enabling autonomous decision-making based on local contextual data.
- **Task 3 – Simulate and test logistics scenarios** using **AMRs**, allowing evaluation of alternative coordination strategies under controlled conditions.
- **Task 4 – Validate the model in real industrial environments** and evaluate its impact on throughput and workstation-level OEE.
- **Task 5 – Synthesize results** into a generalized framework for **adaptive and scalable production logistics control.**

The relationship between the research questions (**RQ**) and the defined research **tasks** is summarized in Table 1, and further elaborated in Chapter 4 through cross-publication analysis. Each task contributes to answering one or more research questions, ensuring comprehensive coverage of both conceptual and practical aspects of the proposed system.

Table 1. Mapping of research tasks to research questions.

RESEARCH TASK	RQ1	RQ2	RQ3	RQ4	PUBLICATION
TASK 1: DESIGN A DIGITAL TWIN MODEL	✔		✔		I, V
TASK 2: DEVELOP AI-BASED CONTROL LOGIC	✔		✔		IV, VI
TASK 3: SIMULATE WITH AMRs	✔	✔		✔	II, III, VI
TASK 4: VALIDATE IN PRODUCTION		✔	✔	✔	VII, VIII
TASK 5: SYNTHESIZE INTO A MODEL				✔	-

By organizing the research around these objectives, questions, and tasks, the thesis guarantees a systematic approach to creating and assessing a decentralized production digital optimization and control model system.

1.3 Scope and Limitations

This doctoral research focuses on integrating intelligent digital optimization and control models with production optimization in discrete manufacturing settings. The study emphasizes shop-floor operations, where coordinating material transport with workstation readiness is crucial to maintaining continuous flow and high operational efficiency.

Four key elements define the thesis:

- **Development of a decentralized control architecture** based on digital twins and AI.
- **Application of autonomous mobile robots (AMRs)** to manage intralogistics tasks at the workstation level.

- **Performance assessment** through indicators such as OEE, workstation idle time, and throughput time.
- **Validation across real-world use cases and industrial pilots** across the chemical, food, wood, apparel, and metalworking industries.

Several limitations are also acknowledged. The proposed model is specifically designed for discrete manufacturing and may not be suitable for continuous or batch processing industries. Successful implementation depends on structured, real-time production data, which is often lacking in legacy systems. The research does not address enterprise-wide planning tools, such as Enterprise Resource Planning (ERP) or MES, beyond their role as interfaces with the digital twin infrastructure. Moreover, while the model supports AI-based local decision-making, global system-wide optimization across multiple factories is outside its scope. Lastly, the validation scenarios involve only a few partner companies and may not fully represent the diversity of the entire manufacturing sector.

To provide clarity, the main boundaries of the study are summarized in Table 2, which highlights the areas included in the scope and those explicitly excluded.

Table 2. Scope and limitations of the research.

In Scope	Out of Scope
Decentralized control model	Enterprise-wide ERP/MES
AI-based local decision-making	Global optimization across factories
Digital twins for real-time data	Process industry applications
AMRs for intralogistics	Legacy data integration challenges
Validation in real factories	Large-scale generalization

This focused scope enables an in-depth investigation of decentralized, AI-driven production control and its practical feasibility. At the same time, it outlines clear boundaries for the model's applicability and identifies areas where future research is needed, particularly in extending scalability and interoperability to broader industrial domains and multi-line production systems.

1.4 Research Methodology Overview

This doctoral research employs a mixed-method approach that combines design science, simulation modeling, and empirical validation in industrial settings. The main goal is not only to develop a theoretical framework but also to iteratively design, implement, and evaluate a decentralized control model that enhances synchronization between production logistics and shop floor operations. To accomplish this, the research utilizes a set of complementary methodological components, each addressing a key aspect of the development process. These components ensure that the proposed model is both conceptually rigorous and practically applicable.

The methodology consists of the following key elements:

- **Digital Twin Modeling:** Virtual replicas of the production environment are created to reflect real-time operational conditions, including workstation statuses, buffer levels, and material routes. These models are constructed using 3D simulation tools and factory-specific data inputs.

- **Data Acquisition and OEE Tracking:** Real-time data is collected from production systems to calculate key performance indicators (KPIs) such as availability, performance, and quality. Besides supporting continuous performance monitoring and OEE-based decision-making, this real-time data stream also constantly updates and strengthens the digital twin, ensuring its virtual state accurately reflects the physical production environment.
- **AI-Based Decentralized Control:** Autonomous agents-representing machines, buffers, or mobile robots-make localized decisions based on AI logic. These include rule-based heuristics, clustering algorithms, and feedback loops to support adaptive coordination.
- **Simulation-Based Testing:** Various logistics scenarios are tested in a controlled simulation environment to explore system behavior under different workloads, identify bottlenecks, and optimize task allocation strategies.
- **Validation in Industrial Case Studies:** The proposed model is tested and evaluated in real-world manufacturing settings, encompassing the chemical, food, wood, apparel, and metalworking industries. Performance improvements are quantified by comparing baseline results (manual or centralized coordination) with those of the AI-based system.
- **Cross-Publication Synthesis:** Insights from 8 peer-reviewed scientific publications are consolidated into a validated framework. Each article addresses specific elements of the architecture, including model design, algorithm development, and industrial deployment.

Each of these elements serves a specific purpose in the research process: digital twins act as a testing environment for model design, data collection ensures decisions are based on evidence, AI logic enables autonomy and flexibility, simulation provides a controlled setting for evaluation, and industrial validation connects the results to real-world practice.

The research methodology follows an iterative and practice-oriented cycle, as illustrated in Figure 3.

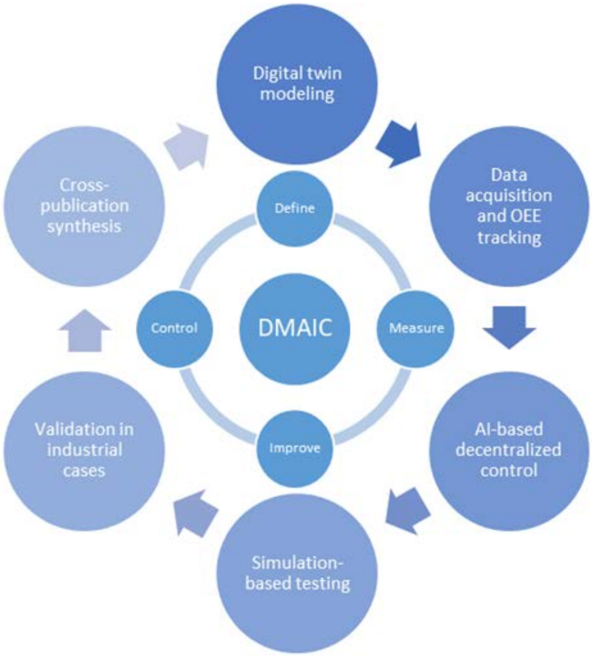


Figure 3. The research methodology cycle and DMAIC integration were employed in the dissertation (T. Raamets).

In addition to the core methodological elements, the research process is structured around the DMAIC cycle, which provides a systematic framework for iterative development and validation. Originating from Six Sigma, DMAIC ensures that problem identification, solution development, and empirical testing follow a disciplined and repeatable process [22,23]. Applying this cycle kept the research closely aligned with both industrial needs and academic rigor, ensuring that improvements remained continuously grounded in measurable results. In the **Define** phase, the primary challenges in production logistics were identified, including material shortages, idle time, and unbalanced workflows. This was followed by establishing clear transformation objectives in collaboration with industrial partners. The **Measure** phase focused on collecting real-time production data—such as workstation idle times, transport delays, and OEE losses—to establish a quantitative baseline of existing inefficiencies. During the **Analyze** phase, simulation experiments and clustering techniques were used to identify bottlenecks, systemic weaknesses, and opportunities for improvement within the production process. The **Improve** phase involved designing and refining AI-based decentralized control logic, testing alternative coordination strategies in digital twin environments, and selecting the most effective solutions for deployment. Finally, the **Control** phase validated the improved system in industrial pilot studies, ensuring sustained performance improvements through continuous monitoring, feedback loops, and adaptive reconfiguration. By embedding DMAIC into the research methodology, the work ensures that each stage of system development—from conceptualization to industrial validation—follows a structured improvement cycle. This enhances both the credibility of the research findings and their practical applicability in real-world manufacturing environments.

1.5 Scientific and Practical Novelty

The novelty of this doctoral research lies in the design and implementation of a decentralized, AI-driven control architecture that integrates digital twin technology with real-time production logistics, enabling more adaptive, efficient, and resilient manufacturing processes. Unlike conventional centralized systems, the proposed approach empowers each production element-such as workstations, buffers, and autonomous transport units-to act as an autonomous decision-making agent while still contributing to system-wide efficiency [24,25]. A further contribution lies in transforming extended OEE from a retrospective performance indicator into a real-time control signal that dynamically triggers decentralized logistics actions, providing a new mechanism for synchronizing production flow with actual workstation conditions.

From a scientific perspective, this work makes several distinct contributions to the academic field:

- **Integration of digital twins with mobile robots** – enabling dynamic adaptation to local production conditions, a capability that remains underexplored in previous research and broadens current understanding of cyber-physical logistics systems.
- **Clustering analysis combined with real-time OEE tracking** – Introducing an interpretable, data-driven system for detecting bottlenecks, optimizing workstation flow, and guiding decentralized operations decision-making.
- **A modular simulation model** – Combining digital twin modeling with AI-based control logic to assess decentralized logistics scenarios before physical deployment, thereby enhancing design science methodology in manufacturing research.
- **Integration of Design Science, digital twin simulation, DMAIC structuring, and industrial validation into a unified methodological framework** – creates a clear, iterative process for developing, testing, and refining decentralized AI-driven control systems. This combined approach has not been previously applied in research on autonomous production logistics, making it a novel methodological contribution of this dissertation.
- **A theoretical contribution to distributed manufacturing control** – aligning decentralized system design with the principles of Industry 5.0, including resilience, adaptability, and human–machine collaboration.

In addition to these scientific advances, the integration of the proposed DMAIC- and Industry 5.0–based technological backbone into real-world production environments enables several practical benefits and innovations:

- **Industrial validation across multiple domains** – including chemical, food, wood, apparel, and metalworking industries, demonstrating robustness and adaptability under heterogeneous operational conditions.
- **Improved operational performance** – including measurable reductions in idle time, improved workstation uptime, increased throughput consistency, and smoother logistics–production synchronization supported by AMR coordination.
- **Real-time decision support for operators** – delivering interpretable insights through OEE-driven triggers, clustering-based diagnostics, and digital twin visualizations that enhance human decision-making consistent with Industry 5.0's human-centric principles.

- **A scalable and cost-efficient pathway for SMEs** – enabling gradual digitalization without demanding replacement of existing MES or ERP systems, thereby supporting wider industry adoption of intelligent decentralized control.

The technical implementation details behind these contributions are presented in Chapters 3 and 4, where the digital twin architecture, DIMUSA data pipeline [26], clustering workflow, and AI-based decision logic are described in depth. Their practical application and validation are further demonstrated in Publications I–VIII. Specifically, the digital twin and data-acquisition architecture are detailed in Publications I and V, the simulation and AMR intralogistics analysis in Publications II, III, and VI, the AI-based control logic in Publication IV, and the full industrial validation in Publications VII and VIII. The combination of these scientific and practical contributions demonstrates that the research is not only conceptually novel but also relevant for real-world manufacturing. The results show that decentralized, AI-enhanced decision-making can simultaneously advance theoretical knowledge and deliver tangible benefits in industrial environments. A summary of the key scientific and practical novelties is provided in Table 3.

Table 3. Summary of scientific and practical novelties.

Scientific Novelty	Practical Novelty
Integration of digital twins with a mobile robot for localized adaptation	Validated in apparel and wood industry use cases
Use of clustering and real-time OEE tracking for decision-making	Improved workstation uptime and throughput time using AMR coordination
Modular simulation combining digital twins and AI control logic	Real-time feedback for human decision-makers
Integration of Design Science, digital twin simulation, DMAIC structuring, and industrial validation into a unified methodological framework	Provides a structured and scalable implementation pathway that supports incremental adoption in real factories
Theoretical contribution to distributed control in Industry 5.0 context	Scalable solution suitable for SME implementation

The proposed method enhances theoretical understanding of decentralized, AI-driven production control and demonstrates tangible benefits in industrial settings. This dual focus highlights the dissertation's substantial contribution to advancing intelligent manufacturing systems, aligning with the broader objectives of sustainable, resilient, and human-centered production within the Industry 5.0 framework.

1.6 Structure of the Thesis

This doctoral thesis is organized into five main chapters, each contributing to the development, validation, and synthesis of a decentralized digital control model for production logistics within the Industry 5.0 framework. The structure follows a logical progression from problem definition and theoretical grounding to methodological design, empirical validation, and synthesis of findings.

The thesis is based on eight scientific publications organized into three thematic clusters: **(1) conceptual and architectural foundations**—Publications I and V; **(2) simulation-based design and optimization**—Publications II, III, and VI; and **(3) industrial validation**—Publications IV, VII, and VIII. Together, these works create a comprehensive foundation that connects theory, simulation, and practice, thereby supporting the overall research framework presented in this dissertation.

The structure of the thesis is illustrated in Figure 4, showing the progression from conceptual foundations through methodology and case-based validation to a generalized model and conclusions.

Figure 4. Structure of the doctoral thesis.

Additionally, the thesis includes a list of publications, a statement of the author's contributions, abbreviations, references, and an Estonian-language summary. The chosen structure provides a coherent narrative flow: it begins with the identification of research problems and theoretical foundations, progresses through the systematic development and validation of the proposed model, and concludes with its broader implications. This organization guarantees both conceptual rigor and practical relevance, while providing readers with a clear overview of how the research objectives are consistently met.

2 Theoretical Background

The development of a decentralized, AI-supported digital optimization and control model for innovative manufacturing environments necessitates a multidisciplinary theoretical foundation. This chapter outlines the key concepts, technologies, and frameworks that inform and support the approach proposed in this dissertation. It begins with an exploration of the Industry 5.0 paradigm, which redefines industrial progress by shifting focus from automation and efficiency alone toward human-centricity, resilience, and sustainability [27]. Within this context, smart manufacturing emerges as a response to the growing demand for production systems that are flexible, adaptable, and aligned with societal objectives. Subsequent sections introduce the core technological and methodological building blocks relevant to modern manufacturing research: production logistics and throughput time management, OEE, the role of AMRs in distributed logistics, the use of DT for real-time monitoring and simulation, and AI techniques used for dynamic decision-making and optimization. Each subchapter outlines the operational challenges faced by contemporary factories and summarizes how existing research addresses these issues through distributed intelligence, autonomous systems, and real-time data integration.

The application of these technologies within the specific decentralized control model developed in this dissertation is described later in Chapters 3 and 4, ensuring that the present chapter focuses solely on the theoretical background and state of the art.

2.1 Industry 5.0 and Smart Manufacturing

Industry 5.0 represents the next evolution of industrial development, building on the technological foundations of Industry 4.0 while reintroducing the human element into advanced manufacturing. While Industry 4.0 emphasized automation, digitization, and cyber-physical systems, Industry 5.0 seeks to establish systems that are not only efficient and data-driven but also sustainable, resilient, and human-centric [28,29]. Whereas Industry 4.0 primarily focused on cyber-physical integration, automation, and data-driven optimization, Industry 5.0 extends this paradigm by explicitly addressing societal and human-oriented goals. It marks a shift from technology-driven transformation toward purpose-driven industrial ecosystems, where resilience, sustainability, and human empowerment become equally important alongside productivity. This evolution highlights not only technological advancement but also the strategic reorientation of manufacturing toward long-term societal value. The European Commission defines Industry 5.0 as a vision in which technological advancements serve broader societal goals, aligning productivity with worker well-being and environmental responsibility [30]. This encompasses integrating technologies such as artificial intelligence (AI), digital twins, and collaborative robotics, which not only optimize production but also foster adaptable processes that empower human workers to be more effective. The three foundational principles of Industry 5.0 are human-centricity, resilience, and sustainability [31]. As illustrated in Figure 5, Industry 5.0 promotes talent and empowerment, ensures adaptability and robustness through flexible technologies, and respects environmental limits while advancing sustainability.

Key principles of Industry 5.0 include:

- **Human-centricity:** Systems are designed to support human workers, providing decision support, customization, and ergonomic features that enhance user experience.
- **Resilience:** Production systems must be able to adapt to disruptions, such as supply chain volatility or rapid market changes.
- **Sustainability:** Emphasis is placed on reducing waste, improving energy efficiency, and designing circular production models that minimize environmental impact.

The human-centric dimension of Industry 5.0 goes beyond ensuring worker safety and well-being. It emphasizes co-creation of value, where human operators and intelligent systems collaborate in decision-making. In this context, artificial intelligence functions as a co-pilot rather than a replacement, augmenting human skills with predictive insights and adaptive support. This principle ensures that technological development empowers rather than displaces the workforce, thereby reinforcing the human role in smart factories.

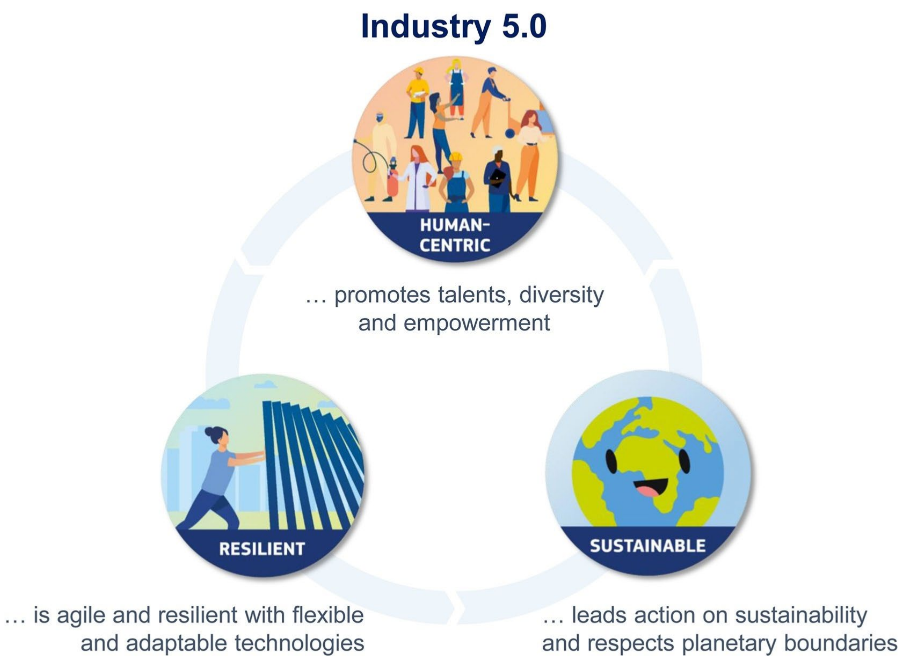


Figure 5. Core values of Industry 5.0 [31].

In the context of smart manufacturing, these principles are operationalized through the collection of real-time data, predictive analytics, and autonomous systems that respond to dynamic conditions. Innovative manufacturing environments rely heavily on intelligent control systems that integrate information from various sources—machines, sensors, and humans—and act upon it in near real-time [32].

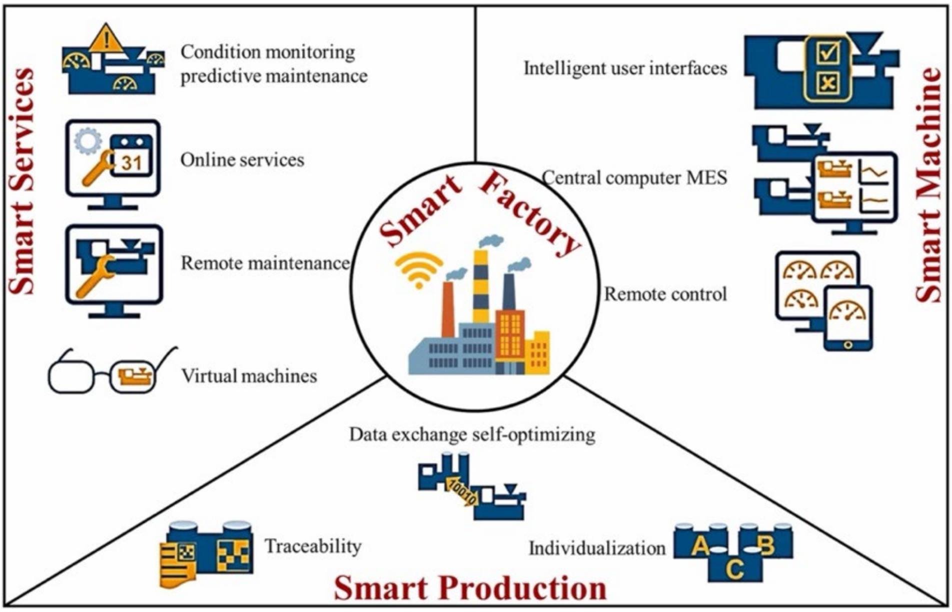


Figure 6. Schematic diagram of the components of a smart factory [32].

The principles of Industry 5.0 are clearly reflected in the model presented in this dissertation. Resilience is achieved through decentralized, agent-based decision-making that enables production systems to respond quickly to disruptions. Sustainability is emphasized by optimizing resource use, reducing idle time, and minimizing unnecessary transportation through AI-driven logistics coordination. Human-centricity is supported via the system's Smart Services layer (as shown in Figure 6), which offers operators real-time performance feedback, visual analytics, and decision support tools. This approach ensures that humans remain central to supervision, interpretation, and strategic management. Therefore, the dissertation advances not only the technological foundation of Industry 5.0 but also its broader societal objectives.

The contribution to Industry 5.0 involves demonstrating how digital twins and AI can be used to implement decentralized, disturbance-responsive control on real shop floors. This is illustrated through tangible improvements in material flow synchronization across the industrial use cases.

2.2 Lean Manufacturing Principles

Lean manufacturing is a philosophy and systematic approach to improving production efficiency by eliminating waste, optimizing value streams, and continuously improving work processes [33]. Originating from the Toyota Production System, Lean principles have become a foundational framework for operational excellence across various manufacturing sectors [34]. Lean manufacturing provides not only a philosophy of efficiency but also a structured set of principles that directly address inefficiencies in production and logistics. For this research, Lean principles are not considered in isolation, but as a framework that can be integrated with digital technologies such as DT, OEE, and AMRs. This integration allows Lean thinking to evolve from a primarily organizational philosophy into a digitally supported, data-driven methodology that supports real-time decision-making and decentralized logistics control [35]. In particular, **five core Lean**

principles form the foundation for structuring the proposed model, including: **value identification**, which defines what truly creates value from the customer's perspective; **value stream mapping**, which analyzes and visualizes every step of the production process to eliminate non-value-adding activities; **flow optimization**, aimed at ensuring a smooth and continuous production flow by reducing waiting times and bottlenecks; **pull-based systems**, which focus on producing only what is needed, when it is needed, thereby minimizing inventory and overproduction; and finally, the **pursuit of perfection**, which establishes a culture of continuous improvement (*Kaizen*) across all organizational levels. Central to Lean manufacturing is the **reduction of waste**, which is classified into eight categories: defects, overproduction, waiting, non-utilized talent, transportation, inventory, motion, and extra processing.

In the context of this research, several Lean principles are embedded within the decentralized digital logistics system through the integration of **AMRs**, **digital twins**, and **OEE-based monitoring**. Within the proposed model, **waste reduction** is achieved by minimizing idle time and unnecessary transport movements, which are automatically detected and addressed through **real-time feedback from the digital twin**; **flow optimization** is supported by **AMRs** that dynamically respond to production needs, ensuring just-in-time material delivery and minimizing workstation waiting times; **standardization** is established via **agent-based digital twins**, which apply consistent logic in requesting and executing logistics tasks; and **continuous improvement** is sustained through **OEE tracking**, which highlights losses in availability, performance, and quality, providing data for iterative process optimization and enhancement.

Table 4 illustrates how key Lean principles are mapped to elements of the proposed digital optimization and control system.

Table 4. Mapping of Lean principles to the optimization and control model.

Lean Principle	Digital Logistics Implementation
Waste reduction	Real-time identification of transport and idle-time inefficiencies via OEE and digital twin monitoring
Flow optimization	AMRs autonomously coordinate material delivery to ensure uninterrupted production flow.
Standardization	Digital twin agents use predefined control logic and communication protocols.
Pull-based operations	Workstations initiate logistics requests based on real-time production needs.
Continuous improvement	OEE-based analytics provide feedback loops for system tuning and improvement.

While Lean principles have been applied in digital manufacturing contexts before, previous research has typically focused on centralized scheduling, predefined rules, or standalone analytics tools [36]. Few studies combine Lean flow principles with a decentralized, agent-based logistics system that responds to real-time OEE signals and digital twin feedback. The innovation in this dissertation is operationalizing Lean principles—such as waste reduction, pull-based flow, and continuous improvement—within a distributed, AI-supported control model in which workstations and logistics units function as autonomous agents. This approach extends traditional Lean methods by enabling real-time, data-driven responses that adapt dynamically to disruptions and variability on the shop floor.

By integrating Lean principles into the digital optimization and control model, the research ensures that the system stays focused on value creation, continuous flow, and waste reduction, even as new technologies are introduced. The synergy between Lean thinking and digital tools, such as AMRs, digital twins, and AI-based decision logic, enables production systems to respond more quickly, manage resources more effectively, and sustain long-term improvements [37]. Therefore, the Lean framework is not only aligned with the goals of Industry 5.0 but also offers a practical structure for embedding waste reduction, flow optimization, and continuous improvement into the proposed decentralized control system.

2.3 Production Logistics and Throughput Time

Production logistics plays a critical role in ensuring the smooth, continuous flow of materials, components, and finished goods throughout the manufacturing process. It involves the planning, execution, and control of all intralogistics activities, including the supply of raw materials to workstations, handling of intermediate products, and movement of finished goods within the factory [38,39].

One of the key performance indicators in production logistics is throughput time, the total time it takes a product to move through the entire production process, from the release of raw materials to the completion of the final product. Throughput time is directly influenced by factors such as material availability, workstation readiness, transport system responsiveness, and task coordination [40,41].

To precisely analyze and improve production logistics efficiency, throughput time (TT) must be clearly defined and monitored. Throughput time is the total elapsed time required for a product to pass through the entire production system—from the release of raw materials to the completion of the finished product. This metric is crucial for identifying bottlenecks and inefficiencies in both production and intralogistics flow[42].

Throughput can be expressed with the following formula:

$$TT = T_{process} + T_{quality} + T_{transport} + T_{waiting} \tag{2.1}$$

In Equation (2.1) [43] T_p Is process time, T_q Is quality inspection time, T_t Is transportation time, and T_w It is the waiting time.

This decomposition enables more targeted analysis and optimization of each component in the total time.

In traditional production systems, logistics planning is often centralized and prescheduled, resulting in inflexible operations that struggle to adapt to disturbances on the shop floor [44].

Common issues in traditional production systems include **delayed material delivery or removal**, which leads to idle workstations; **overloaded buffers**, which obstruct transport systems and reduce process visibility; and **bottlenecks** arising from misaligned timing between production and logistics activities [45,46].

These inefficiencies not only increase throughput time but also negatively impact OEE, which reflects how well a manufacturing system utilizes its resources in terms of availability, performance, and quality.

To address these challenges, modern production systems increasingly adopt real-time, decentralized logistics control, where decisions about material flow are made dynamically based on current conditions. In such systems, each production unit (such as a workstation or AMR) functions as an intelligent agent capable of communicating its needs, monitoring local status, and independently requesting or executing logistics actions [47].

This thesis builds on this concept by proposing a decentralized digital optimization and control model supported by digital twins and artificial intelligence [48]. The goal is to reduce idle time at workstations, minimize transport delays, and ultimately improve throughput time. By combining real-time data with autonomous control, the system enables more responsive and balanced production flows, which are essential for high-performance Industry 5.0 environments.

2.4 Overall Equipment Effectiveness (OEE)

OEE is one of the most widely recognized performance indicators in manufacturing, providing a quantitative measure of how effectively a production system utilizes its resources [49]. Initially introduced by Seiichi Nakajima as part of the Total Productive Maintenance (TPM) framework in the 1980s, OEE has since evolved into a global benchmark for assessing production efficiency across industries [50,51]. The metric combines three dimensions-availability, performance, and quality-into a single index that highlights both technical and organizational losses. Availability reflects the proportion of scheduled time the equipment is operational; performance measures the actual output speed relative to the designed capacity; and quality accounts for the ratio of good units produced relative to the total [52]. By capturing these aspects simultaneously, OEE provides a comprehensive view of equipment utilization and productivity bottlenecks [53,54].

It is calculated as the product of three core components:

- Availability: The percentage of scheduled time that the equipment is available for production (i.e., no breakdowns or waiting for materials).
- Performance: The speed at which the process operates as a percentage of its designed capacity.
- Quality: The proportion of good units produced out of the total output.

Equation (2.2) [55] is typically expressed as:

$$OEE = (A) \times (P) \times (Q) \tag{2.2}$$

Where,

$$Availability(A) = \frac{Planned\ production\ time - unplanned\ downtime}{Planned\ Production\ Time} \tag{2.3}$$

$$\text{Performance(P)} = \frac{\text{Actual amount of production}}{\text{Planned amount of production}} \tag{2.4}$$

$$Quality(Q) = \frac{Actual\ amount\ of\ production - non\ acepted\ amount}{Actual\ Amount} \tag{2.5}$$

It is particularly relevant in high-mix, low-volume environments, where frequent changeovers and material-handling disruptions significantly affect productivity [56,57]. Traditional OEE implementations, however, focus mainly on machines or production lines and often overlook logistics-induced downtime [58].

In the proposed control model, OEE values are calculated in real time at the workstation level and used as an active control signal. For example, when availability drops due to missing input materials, an urgent transport request can be triggered to an AMR. Similarly, if buffers are full, OEE feedback can reprioritize AMR tasks to remove excess items. By embedding OEE into the decision-making loop, the system transforms the metric from a retrospective performance measure into a dynamic driver of decentralized optimization.

The application of dynamic, data-driven OEE calculations facilitates intelligent decision-making and adaptive logistics flow control, aligning with the decentralized architecture advocated in Industry 5.0 systems. Moreover, by integrating OEE feedback directly into the control loop, the system can continuously self-optimize, proactively address bottlenecks, and maximize workstation utilization.

To highlight the conceptual differences, Table 5 compares the traditional OEE calculation with the extended OEE approach developed in this research, which explicitly integrates logistics-related downtime and real-time data into the metric.

Table 5. Comparison of Traditional OEE and Extended OEE (logistics-inclusive).

Aspect	Traditional OEE	Extended OEE in this research
Scope	Machine or production line	Workstation + logistics units (AMRs, buffers)
Data basis	Equipment uptime and quality metrics	Real-time OEE + transport status + buffer conditions
Focus	Retrospective efficiency analysis	Proactive logistics-driven control signal
Bottleneck coverage	Breakdowns, speed losses, quality defects	Includes logistics delays, waiting, and congestion
Application	KPI for monitoring and improvement programs	Real-time optimization of intralogistics and flow

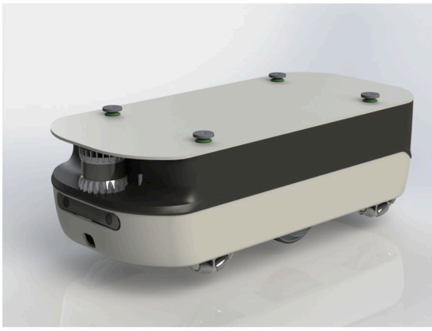
As shown in Table 5, the extended OEE not only measures equipment efficiency but also functions as a control signal for decentralized logistics coordination, making it a cornerstone of the proposed optimization model. OEE decomposes losses into availability, performance, and quality. In discrete manufacturing, the largest share of availability loss frequently originates from logistics-induced starvation and blocking (i.e., empty input buffers and full output buffers). Treating OEE as a live signal, therefore, provides a direct control handle for intralogistics: when availability drops due to input starvation, an AMR mission is triggered; when blocking is detected, it is removed as a priority. In this way, OEE ceases to be a retrospective KPI and becomes a proactive driver for AMR task generation and routing.

By integrating OEE into the digital twin and AI-driven architecture, the research aligns with Industry 5.0 principles of adaptability, resilience, and human-centricity. The dynamic application of OEE not only improves equipment utilization but also enhances material flow coordination, making it a cornerstone of decentralized production control and a practical enabler for Industry 5.0 logistics optimization.

2.5 Autonomous Mobile Robots (AMRs) in Manufacturing

AMRs have emerged as a key enabler of flexible and intelligent material handling in modern manufacturing environments [59]. Unlike Automated Guided Vehicles (AGVs), which follow predefined paths, AMRs use onboard sensors, cameras, and AI algorithms to dynamically navigate factory floors, avoid obstacles, and make autonomous routing decisions [60]. These features make them well-suited to modern manufacturing environments characterized by frequent layout changes and variable tasks.

Figure 7 shows the AMRs applied in this research for simulation and experimental validation.



a)

b)

c)

d)

Figure 7. Examples of Autonomous Mobile Robots (AMRs) used in research and industrial case studies: a) Boxbot (TalTech prototype), b) MiR100, c) Robotnik RB-2, d) Robotino.

The adoption of AMRs is particularly relevant in discrete manufacturing, where production volumes, product variants, and layout configurations change frequently. AMRs offer a scalable, adaptable alternative to traditional conveyor systems or manual transport, enabling just-in-time (JIT) delivery of materials and parts without extensive infrastructure [61].

Key benefits of AMRs in production logistics include:

- **Decentralized decision-making:** AMRs can assess their current environment and make routing or task decisions independently,
- **Real-time responsiveness:** They can reprioritize tasks or reroute based on live conditions (e.g., workstation status or transport congestion),
- **Flexible task allocation:** AMRs can be assigned dynamically to pick up, deliver, or transfer goods as needed,
- **Reduced downtime:** Intelligent coordination between AMRs and workstations can help minimize idle time due to delayed deliveries or full buffers.

In this research, AMRs are used as mobile agents within a decentralized digital control system. Each AMR functions as both an executor and a decision-maker, receiving input from digital twins and OEE monitoring to determine where and when to deliver or pick up materials. Unlike traditional centralized dispatching, the agent-based approach enables each AMR to evaluate multiple requests simultaneously, negotiate task priorities, and independently adapt to changing shop floor conditions [62]. Several of the industrial case studies presented in this dissertation, especially those in the food manufacturing sector, demonstrate how AMRs contribute to notable improvements in throughput, workstation availability, and resource efficiency [63,64]. Integrating AMRs with lean-inspired scheduling reduced idle time and improved the balance between material inflow and outflow, confirming their effectiveness in high-variance production environments [65]. An additional example of the simulation data used in this research is provided in Appendix 9. The proposed system extends beyond simple dispatching by incorporating AI-based coordination logic that enables AMRs to dynamically adjust their routes, reprioritize deliveries, and share real-time status information with workstations. This capability is strengthened by their integration with digital twin platforms, which simulate congestion risks, buffer status, and material demand in advance, allowing for predictive rather than purely reactive decision-making [66].

Furthermore, simulation environments were created to assess AMR performance under different load conditions, energy limits, and control strategies. These simulations not only guided model adjustments but also provided insights into safety issues, task allocation efficiency, and resilience in the face of unexpected disturbances [67]. Such testing confirmed that decentralized coordination enhances scalability and decreases dependence on rigid pre-planned schedules. The integration of AMRs as autonomous control units within the digital twin architecture enables decentralized task execution and real-time coordination across the production system. Their behavior is synchronized with the digital twin, ensuring that transport tasks are assigned based on current system conditions without relying on centralized scheduling. The practical application of these principles in the industrial case studies of this dissertation is presented in Chapters 3 and 4.

2.6 Digital Twins and Simulation-Based Optimization

DTs are virtual representations of physical assets, systems, or processes that are continuously synchronized with real-world data. Unlike traditional simulation models, which are static and primarily used for offline analysis, modern DTs are dynamic, predictive, and adaptive, enabling real-time closed-loop optimization of manufacturing processes [68].

In manufacturing, DTs serve multiple roles: they enable scenario testing without disrupting actual production, provide real-time transparency into machine and logistics states, and support predictive decision-making [69]. When combined with advanced AI algorithms, DTs evolve from passive replicas into active decision-support systems, capable of optimizing resource allocation, scheduling, and flow control [70,71].

The digital twin concept enables simulation and forecasting, allowing virtual models to test alternative scenarios and predict the impact of changes without disrupting real production. Through real-time synchronization, the digital twin continuously receives live data from the shop floor, accurately reflecting the current state of machines, workstations, and logistics flows. This integration supports closed-loop optimization, enabling control systems to act on insights from the digital twin to dynamically adjust and improve operations in real time. As illustrated in Figure 8, the Deloitte Digital Twin [72] model conceptualizes the bidirectional interaction between the physical and digital environments, emphasizing continuous data exchange and analytics-driven optimization.

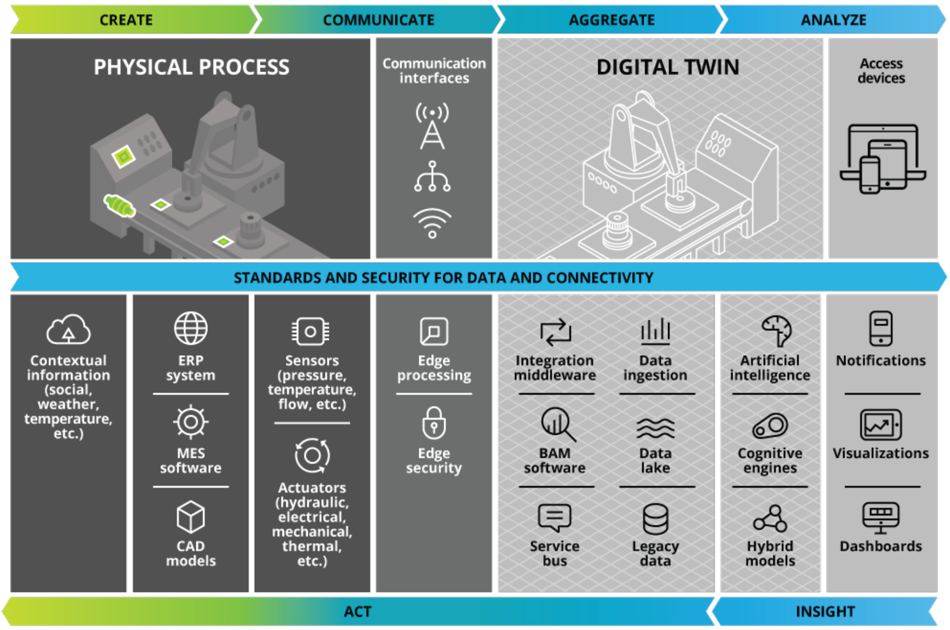


Figure 8. Deloitte Digital Twin model [72].

In this research, DTs were developed to model workstations, buffers, and autonomous mobile robots (AMRs) as intelligent agents, each with local control logic. This agent-based representation contrasts with traditional hierarchical MES, enabling decentralized decision-making that improves responsiveness, scalability, and fault tolerance. The simulation-based optimization framework further enables the evaluation of logistics strategies, buffer sizing, and AMR routing under varying workloads, before implementation in real factories. Each element in the production system-whether a machine, workstation, or robot-is modeled as an autonomous agent within a digital twin framework. These agents operate under agent-based control logic, allowing them to make local decisions based on real-time status and input. They communicate and coordinate with other agents—for example, by requesting material delivery or reporting idle time—and collectively enhance overall system efficiency through distributed intelligence and adaptive interaction.

The digital twin platform developed in this research serves both as a **monitoring tool** and a **simulation environment** for **validating** logistics coordination strategies. Combined with real-time OEE tracking and AI algorithms, it forms the technological backbone of the decentralized production control system proposed in this dissertation. Beyond monitoring, the platform embodies the evolution of digital twins into **adaptive** and **predictive systems**. It enables proactive logistics planning, energy-efficient scheduling, and continuous flow optimization, while also supporting operators through improved transparency and decision support. The integration of digital twins and agent-based control enables the creation of intelligent production systems that can autonomously respond to unexpected events like machine failures or material delays, continuously optimize operations with live data, and reduce the need for human intervention in routine tasks decision-making.

In this way, the platform not only enhances decentralized coordination but also demonstrates the principles of Industry 5.0, such as adaptability, resilience, and human-machine collaboration.

2.7 Artificial Intelligence in Decentralized Control

Artificial Intelligence (AI) has become a central enabler of the evolution of modern manufacturing systems. In production control, AI enhances decision-making, automates complex tasks, and enables systems to learn and adapt based on both historical and real-time data [73]. Compared to rule-based or deterministic systems, AI-driven control enables the prediction of bottlenecks before they occur, optimizes scheduling and task allocation, learns from historical performance, and allows for localized, autonomous decisions even under uncertain or incomplete information [74]. In recent years, several dominant trends have shaped the application of AI in manufacturing [75]. Predictive analytics and anomaly detection are increasingly used to anticipate disturbances and improve system resilience [76,77]. Optimization techniques, including combinatorial Dijkstra's algorithm, heuristic and metaheuristic methods such as genetic algorithms (GAs), and ant colony optimization (ACO), are applied to material flow and AMR routing problems [78,79]. Meanwhile, clustering and classification approaches, such as k-means and DBSCAN, support interpretable diagnostics by identifying patterns in systemic inefficiencies [80,81]. In addition, recent studies emphasize that modern production environments increasingly rely on heterogeneous, distributed data sources, which must be integrated into a unified decision-making framework to enable decentralized intelligence [82]. Such findings reinforce the need for AI-driven control architectures capable of operating on fragmented, multi-layered, and dynamically changing datasets. These trends provide the theoretical foundation for this research, in which AI is embedded not as a centralized optimizer but as independent agents operating within a decentralized control architecture.

Logistics Agents

Logistics agents are responsible for coordinating material flow using AMRs. Each agent evaluates local conditions: task urgency, workstation buffer status, and AMR availability. It assigns missions according to a weighted cost function in Equation (2.6) [83]:

$$\mathrm{f}(\mathrm{i},\mathrm{j}) = \alpha \cdot d(\mathrm{i},\mathrm{j}) + \beta \cdot t_{\mathrm{j}} + \gamma \cdot o_{\mathrm{j}} \tag{2.6}$$

Where $d(i,j)$ is the travel distance of the AMR i to the workstation j, and t_j is task urgency derived from idle-time signals, and o_j is the operational load of the workstation j.

To compute the shortest path corresponding to the distance component $d(i,j)$, a classical Dijkstra algorithm was used. Given a graph $G = (V,E)$ of navigation nodes and weighted edges, Dijkstra's method (2.7) [84] determines the minimum-cost path by iteratively relaxing edges according to:

$$\mathrm{D(v)} = \ min\big(\,\mathrm{D(v)},\ \ \mathrm{D(u)} +\ \mathrm{w(u,v)}\big) \tag{2.7}$$

Where $D(v)$ is the shortest known distance from the source node to the node v, $\mathrm{w(u,v)}$ is the weight (time or distance) of the edge (u,v) and u predecessor node currently under evaluation. The algorithm proceeds by initializing $D(source) = 0$ and all others $D(v) = \infty$, then extracting nodes from a priority queue ordered by current distance. All outgoing edges are relaxed until the shortest path tree is complete. As described in Publication VI, Dijkstra provides a favourable balance between computational efficiency and routing accuracy in dynamic factory environments [85]. Its time complexity is expressed as:

$$O(E + N\log N) \tag{2.8}$$

Where N is the number of navigation nodes and E the number of edges in the graph. Simulation studies demonstrated that a **Dijkstra-based path search** provided the best balance between computational efficiency and responsiveness in dynamic factory environments, outperforming more complex metaheuristics such as GA and ACO in terms of real-time applicability [86,87].

OEE Monitoring Agents

As introduced in Section 2.4, OEE is a comprehensive measure that combines availability, performance, and quality. In this research, OEE is extended from a retrospective KPI to an **active control signal**. Each workstation agent continuously monitors its OEE, particularly availability losses related to logistics delays.

To make these signals actionable, clustering methods were applied to both historical and real-time OEE datasets. Using **k-means clustering**, workstations were grouped into categories such as stable, bottleneck-prone, or underutilized:

$$E\ = \sum_{i=1}^{k} \sum_{x \in S_i} \left|\left|x\ -\ \mu_i\right|\right|^2 \tag{2.9}$$

In Equation (2.9) [88], E denotes the objective function measuring the total within-cluster variance. S_i represents the set of data points belonging to the cluster i, and μ_i is the centroid (mean vector) of the cluster i . $|S_i|$ indicates the number of data points in the cluster i, and $\left|\left|x\ -\ \mu_i\right|\right|$ denotes the Euclidean distance between a data point x and its cluster centroid.

$$\mu_i = \left(\frac{1}{|S_i|}\right) \sum_{x \in S_i} x \tag{2.10}$$

In Equation (2.10), the centroid μ_i of the cluster i is calculated as the mean of all data points assigned to that cluster.

To improve robustness, **DBSCAN** was used to filter anomalies and irregular downtime patterns. These clusters provided interpretable triggers for logistics agents-for example, if a group of stations exhibited recurring availability losses, AMR tasks were reprioritized accordingly. This transformation of OEE from a monitoring tool to a **real-time decision input** was validated in an apparel industry case study [89].

Contribution to Throughput Improvement

As described in Section 2.3, throughput time (TT) is a key metric for evaluating the efficiency of production flow. The integration of AI-based logistics and OEE agents contributes directly to TT reduction by:

- decreasing workstation idle time through just-in-time material supply,
- balancing workloads across stations using clustering-based insights,
- reducing transport delays through adaptive AMR task allocation.

The combined effect is improved flow stability and higher overall OEE across the production network.

Justification of Selected AI Approaches

The chosen algorithms and control strategies were selected according to three main criteria:

- **Industrial feasibility:** Computationally efficient and interpretable methods (Dijkstra for routing, k-means for clustering) were favored over complex black-box models.
- **Adaptability:** Weighted cost functions and clustering-based thresholds support real-time adjustment under variable conditions.
- **Transparency:** OEE-based triggers and interpretable clusters provide actionable and explainable feedback to human operators, strengthening trust in AI-driven decisions.

By integrating AI agents within a decentralized control framework, the system facilitates real-time coordination between logistics and workstation monitoring. Logistics agents assign AMR tasks based on local conditions, while OEE agents deliver ongoing performance signals that guide task prioritization. The selected algorithms—Dijkstra for routing and k-means for clustering—were chosen for their computational efficiency and transparency, ensuring appropriateness for real-time industrial applications environments.

3 Development and Implementation of a Decentralized AI-Driven Control Model for Production Processes

The research methodology defines the systematic approach used to design, develop, and validate the proposed decentralized control model. Since the aim of this dissertation is not only to advance theoretical understanding but also to demonstrate practical applicability in industrial environments, the methodology combines design science research, simulation-based testing, and empirical case studies. The development steps described in this chapter build directly on the results and methods presented in Publications I–VIII, with each subsection clarifying the specific contribution of the respective papers. This mixed-method approach ensures both conceptual rigor and industrial relevance.

The **design science** perspective was chosen because the central contribution of this work is an artifact—a digital optimization and control model that must be iteratively developed, implemented, and evaluated. Simulation environments offer a controlled setting for developing and evaluating alternative coordination strategies, while industrial case studies facilitate their implementation and validation under real operating conditions.

The methodology is also structured around the **DMAIC** cycle, which provides a disciplined framework for iterative improvement. Each phase corresponds to specific research tasks, from problem definition and data collection to the development of AI-based decision logic and its validation in real factories. This cyclical structure ensures that the results are systematically refined based on empirical feedback and industrial requirements.

By combining these elements-design science, digital twin simulation, DMAIC structuring, and industrial validation- the research methodology creates a clear foundation for reaching the main goal of this thesis: to develop and apply a decentralized AI-based control system that enhances synchronization between production logistics and shop floor operations.

3.1 Research Design

The research employs a design science methodology supported by empirical case studies and simulation-based validation. Its goal is to create a decentralized control model for production logistics and assess its performance in both digital and physical manufacturing settings. **Design science** offers the framework for developing and improving the artifact—integrating digital twins, agent-based logic, and AI-driven decision support—while the DMAIC cycle ensures a systematic progression from problem identification to model refinement validation. Requirement analysis in this research was grounded in real industrial contexts. The system requirements were derived from discrete manufacturing processes across the chemical, food, wood, apparel, and metal industries. In these environments, recurring bottlenecks in material supply and removal were observed, highlighting the need for modular, real-time, and autonomous control mechanisms to reduce idle time and throughput delays. These requirements guided the selection of digital twins, autonomous agents, and AI algorithms as the main enabling technologies for the proposed control model.

As part of the research design, the concept of the **Virtual Factory (VF)** was applied and tested in the chemical industry, focusing on real-time data acquisition and planning using simulation models. The VF represents an early version of the digital twin concept, serving as a virtual environment for testing production behaviors, layout choices, and planning scenarios before implementation in the physical factory. In this study, the VF laid the groundwork for subsequent digital twin development, enabling integrated monitoring of production units, evaluating throughput, lead times, and resource use, and guiding sensor placement and data collection strategies before physical deployment [90]. This approach demonstrated how digital twins can support the alignment of logistics and production processes at an early design stage, ensuring that control mechanisms are virtually validated before deployment in real industrial environments. In addition to the Virtual Factory concept, the **DIMUSA** platform is introduced in the methodology as the primary system for real-time **data acquisition**, **processing**, **and visualization**. While its technical details are discussed later in Chapters 3.3 and 4, it is mentioned here for clarity, as DIMUSA served as the main data integration layer across the industrial use cases. This ensured that machine states, OEE metrics, workstation events, and AMR task logs could be reliably synchronized with the digital twin models and the decentralized control logic. The developed production line model, illustrated in Figure 9, shows how AMRs were integrated into the VF to simulate material flow between workstations and warehouses. This model provided the first empirical basis for testing data-driven logistics coordination in a controlled digital environment.

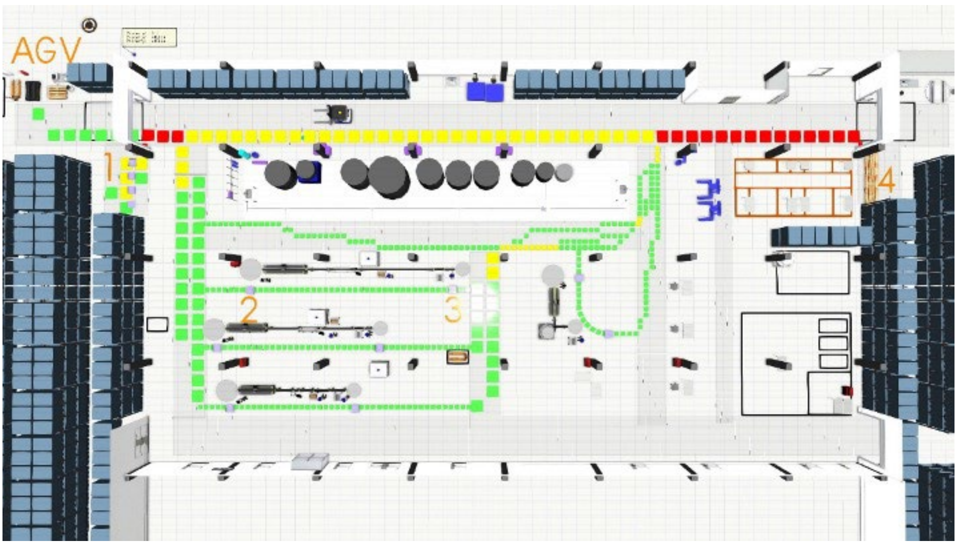


Figure 9. Virtual factory model of a chemical industry production unit, used for real-time data acquisition and simulation of production logistics (adapted from Publication I).

Each of the eight publications that form the basis of this thesis contributed a specific perspective, ranging from simulation-based analysis to industrial validation, allowing both conceptual clarity and practical relevance to emerge from the overall research process. Together, these publications follow the logic of the DMAIC and design science methodologies: early papers address the Define, Measure, and Analyze stages through data acquisition and simulation (Publications I–III), mid-stage works contribute to solution development and improvement through the design and refinement of control logic (Publications IV–VI), and the final papers validate the implemented system in industrial settings, aligning with the Improve and Control phases (Publications VII–VIII).

This structured research design ensured that each phase of the study built directly on the outcomes of the previous one. Problem identification and requirement analysis grounded the work in real industrial challenges, while model development and simulation created a safe environment for iterative testing. The subsequent validation in industrial case studies confirmed the model's applicability under practical constraints. Finally, the synthesis phase integrated findings from all case studies, resulting in a generalized framework for decentralized control.

By combining design science with simulation-driven analysis and empirical validation, the methodology strikes a balance between scientific rigor and industrial relevance. This approach not only enabled the creation of a novel decentralized AI-based control system but also ensured that the solution is transferable, scalable, and aligned with the strategic principles of Industry 5.0. The following sections (3.2–3.6) provide a detailed description of the data sources, modeling tools, validation scenarios, and performance indicators used to implement this research design.

General System Architecture

Based on this foundation, a general system architecture was developed to support decentralized, AI-driven production logistics. As illustrated in Figure 10, the architecture integrates three interconnected layers: (1) the real-time data layer, (2) the AI-based analysis layer, and (3) the virtual-factory simulation layer. Together, these components provide a unified digital twin framework for synchronizing physical operations with analytical and simulation-based decision support.

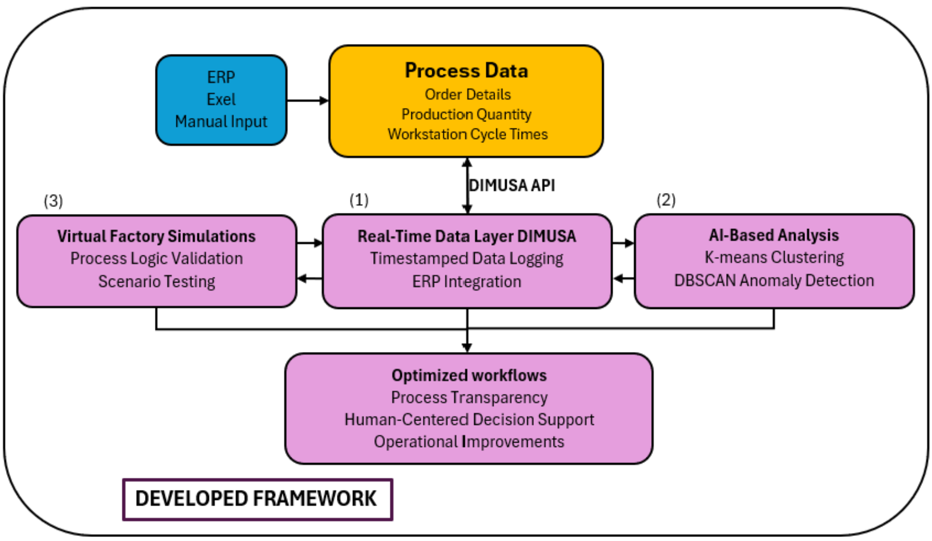


Figure 10. Developed framework for the agent-based digital twin architecture, combining process data, virtual factory simulations, and AI-based analysis to support real-time optimization (adapted from Publication VIII).

The architecture is organized into three interconnected layers:

- **(1) Real-time data layer (DIMUSA).** This layer gathers workstation states, buffer levels, AMR positions, and process events through the DIMUSA connectors. The resulting data stream ensures synchronization between physical and digital assets and supports downstream analytics and simulation workflows. Interfaces with MES and sensor infrastructures enable seamless integration into existing industrial systems environments.

- **(2) AI-based analysis layer.** This layer provides analytical capabilities for monitoring system conditions and supporting decentralized control decisions. It includes performance-tracking components, data-driven diagnostic tools (e.g., clustering), and interfaces to agent-based logic described later in Section 3.4. Although it does not execute decisions at this level, this layer provides the information required by the autonomous agents.
- **(3) Virtual-factory simulation layer.** The virtual factory models workstation behaviour, buffer dynamics, AMR movements, and material flows. It enables scenario testing, early validation of design choices, and iterative refinement of the control logic prior to deployment in real environments.

Through the interaction of these three layers, the system operates as a decentralized architecture where each production unit can function independently while contributing to coordinated system-level performance. The virtual-factory pilot developed for the chemical industry provided an initial environment for testing data-acquisition workflows and assessing the early versions of the digital-twin components before full deployment.

3.2 Digital Twin Architecture and Modeling Tools

At the core of the proposed system lies a modular digital twin architecture that represents each physical component of the production system—such as workstations, buffers, and AMRs—as a virtual agent with embedded logic. This architecture enables decentralized control and real-time decision-making by combining live data streams with simulation models and AI-based algorithms. Earlier studies in the chemical industry demonstrated how the Virtual Factory concept could serve as a foundation for such modeling (Case A – Chemical industry), while later implementations in the wood and apparel industries validated its scalability and adaptability (Case D – Wood industry and Case E – Apparel industry).

The digital twin framework is structured into **three layers** (Figure 10). The **data layer** collects real-time sensor information, including machine states, buffer levels, and AMR locations. The **virtual model layer** mirrors the current state of each physical object, providing a continuously updated representation of the production system. In addition to these, the **control logic layer** includes decision-making mechanisms implemented as rule-based logic or AI algorithms. This separation of concerns provides flexibility, allowing individual layers to be updated or replaced without disrupting the overall architecture.

Within this framework, different types of **agents** assume specific roles and responsibilities. **Workstation agents** continuously monitor their OEE, detect waiting states such as material shortages or blocked buffers, and trigger appropriate requests. **AMR agents** manage transport tasks by receiving and prioritizing requests, navigating dynamically based on real-time floor conditions, and reporting their status back to the system. **Buffer agents** are responsible for tracking capacity levels and forecasting potential congestion, coordinating with both upstream and downstream units to maintain balanced flow. Optionally, a **supervisor agent** can be introduced to aggregate system-wide data for visualization and optimization purposes, while still respecting the decentralized design by avoiding direct hierarchical control. Each agent operates with only partial local knowledge yet contributes to global efficiency through lightweight communication and adaptive behavior. The detailed logic and interaction mechanisms of these agents are explained in Sections 3.4 and 3.5.

Coordination and communication between agents are achieved via a message-passing protocol that transmits task requests, status updates, and OEE-triggered alerts. For example, a workstation agent can issue a request for material delivery, a buffer agent can report congestion, or an OEE agent can signal idle time caused by missing inputs. This event-driven communication approach ensures rapid responsiveness while reducing decision-making latency, particularly in dynamic, variable production environments.

The digital twin and agent system was implemented using a hybrid technology stack. 3D simulation tools, such as Visual Components and Siemens Plant Simulation, were employed for factory layout and material flow modeling (Case A – Chemical industry; Case D – Wood industry). Control logic and decision-making algorithms were implemented in Python-based agent modules, while database interfaces and MQTT communication protocols enabled real-time data integration with physical systems (Case C – Metal industry; Case E – Apparel industry). This hybrid setup enabled both offline simulation-based experimentation and live piloting in industrial environments, ensuring the robustness, transferability, and scalability of the decentralized control model [91].

3.3 Data Sources and Acquisition from Industrial Use Cases

The empirical foundation of this dissertation is based on industrial data collected through collaborative digitalization projects conducted with multiple manufacturing companies. The selected industrial use cases spanned diverse domains, including the chemical, food, metal, wood, and apparel industries, and were explicitly chosen to capture variations in workflows, logistics requirements, and levels of automation maturity. This diversity enabled comprehensive validation of the proposed decentralized digital optimization and control model across heterogeneous industrial contexts.

Across these use cases, several recurring problems were observed that highlighted the limitations of existing production logistics coordination. In the chemical industry (Case A), the main issue was the lack of integrated, real-time data for monitoring material movement and workstation activity. The food industry (Case B) experienced frequent transport delays and unbalanced buffer levels due to manual dispatching and limited synchronization with workstation needs. The metal industry (Case C) exhibited fragmented, inconsistent machine-level data, making it challenging to identify micro-stoppages and low-frequency disruptions. The wood industry (Case D) required early detection of layout bottlenecks during design stages, as physical reconfiguration was costly and time-consuming. The apparel industry (Case E) struggled with high takt variability, manual scheduling, and unstable material supply, resulting in frequent idle periods. These case-specific challenges motivated the development of a decentralized, data-driven control model capable of addressing variability, improving responsiveness, and enhancing flow stability across heterogeneous industrial environments.

Primary Data Categories

Several categories of empirical data were gathered and integrated into the research framework to support modeling, simulation, and evaluation. Real-time shop floor data were collected from controllers and DIMUSA interfaces, including machine states, process parameters, and sensor signals (Table 6). To enable seamless data exchange between the physical and digital layers, DIMUSA was employed as a middleware and integration platform, connecting production assets, sensors, and control logic to the digital twin environment. While the core DIMUSA platform is an existing industrial system, its capabilities were extended in this research through the integration of AI-based decision-support components that enable real-time evaluation of workstation conditions and trigger decentralized logistics actions. This architecture ensured bidirectional communication, allowing virtual models to receive live process data and send control commands back to the shop floor (Figure 11).

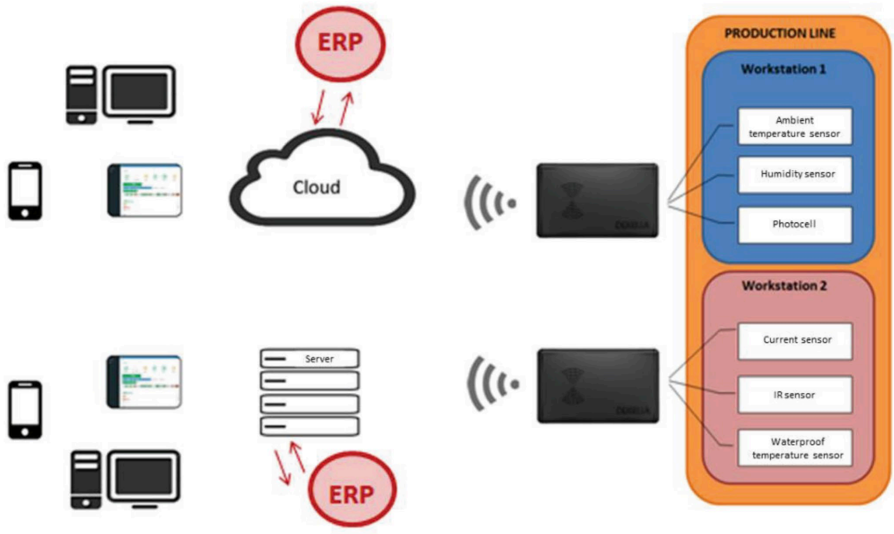


Figure 11. DIMUSA architecture for data integration and real-time synchronization (adapted from Publication V).

Workstation-level OEE metrics-including availability, performance, and quality-were systematically recorded, along with detailed logs of downtime reasons and production losses. In parallel, material handling and logistics data were monitored, such as buffer fill levels, transport lead times, and task queue lengths. To complement quantitative information, qualitative insights were collected through structured observations and semi-structured interviews with operators, logistics staff, and supervisors. In addition to informal feedback collected during pilot stages, formal operator feedback was obtained in Publication VIII, where the DIMUSA-based digital twin interface was deployed in an apparel manufacturing SME. Operators provided direct input on task initiation, task completion logging, and the clarity of workstation status indicators. Their feedback led to refinements in the visualization, such as more transparent reporting of operation start/finish events and improved real-time queue displays. These results, summarized in Table 8, confirm that the user-centric dashboard design supported both operator awareness and decision-making. Finally, historical performance records were utilized for clustering analysis, benchmarking, and validation of the simulation model. A representative example of the collected DIMUSA data structure used in these analyses is presented in Appendix 11.

The data collection process combined automated logging from industrial equipment with manual input in environments with limited digital infrastructure. In several cases, the author designed and implemented custom data pipelines and visualization dashboards, providing real-time monitoring interfaces and facilitating integration with digital twin environments. The feasibility of this approach was first demonstrated in the chemical industry through the Virtual Factory model, where sensor placement strategies and data-integration workflows were validated in a 3D simulation environment before transitioning to fully digital-twin implementation (Publication I).

Table 6. Overview of data sources and collection by case.

Case & sector	Main data types	Volume/horizon	Acquisition method	Use in thesis
Case A – Chemical	Sensor states (ms), line events, buffer status (units per hour)	3 lines, 6–12 months	DIMUSA connectors + custom middleware	Virtual factory + OEE monitoring & AMR simulation (I, III)
Case B – Food	Cycle times (s), AMR task duration (s), buffer levels (units), OEE (%)	8 cells, 3–6 months	Logs + manual time-studies	AMR simulation & KPI eval (II, IV, VI)
Case C – Metal	Workstation OEE (%), micro-stops (s), production orders (units)	5 cells, 3 months	DIMUSA connectors + dashboards	Data analytics & transparency (V)
Case D – Wood	Layout, routing, buffer levels (units), OEE (%)	full line, design stage	CAD + Plant Simulation + samples	Layout sensitivity & clustering (VII)
Case E – Apparel	Live OEE (%), task queues (operation), takt variability (s)	12 stations, 3 months	DIMUSA; operator inputs	Industrial validation & clustering (VIII)

Table 6 summarizes the primary data sources used in the five industrial cases (A–E), covering both simulation and real production environments. Each case contributed different data types—ranging from workstation OEE and micro-stops to AMR telemetry and buffer dynamics—which served as the empirical foundation for model development, simulation, and validation across Publications I–VIII. Representative data structures related to these cases are provided in Appendices 9–11:

- **Appendix 9** – Visual Components simulation data used in the Chemical industry case (Case A), supporting Publications I and III. Publication II also uses simulation but based on the Food industry model.
- **Appendix 10** – DIMUSA AMR telemetry and mission-control data used in Case B AMR deployment (Publications IV and VI).
- **Appendix 11** – DIMUSA workstation-level OEE and flow-monitoring data used in Case C, Case D, and Case E for clustering and layout analysis (Publications V, VII, and VIII).

Together, Table 6 and Appendices 9–11 provide a complete overview of the data landscape supporting the decentralized control model and its industrial validation.

3.4 Simulation and AMR Motion Optimization Development

A central innovation of this research is the use of real-time OEE feedback as a control signal within the decentralized logistics system. Unlike conventional approaches, where OEE serves only as a retrospective KPI, it becomes an active input for decision-making by intelligent agents here. This enables the system to detect performance losses dynamically and initiate corrective actions in real time. The approach was validated in several simulation environments and later in industrial pilots (Publications IV, VI, VIII).

Real-Time OEE Monitoring

Each **workstation agent** continuously monitors its performance using three components: **availability,** which indicates downtime caused by material shortages or buffer blockages; **performance**, which shows deviations from expected cycle times; and **quality**, which measures the percentage of rejected or defective parts. These metrics are calculated locally and stored in the workstation agent's status memory. Predefined thresholds turn OEE deviations into triggers for corrective actions-for example, requesting urgent material delivery when availability drops, alerting **AMR agents** to prioritize buffer removal during congestion, or suggesting diagnostic checks when cycle times increase. This closed-loop system allows each agent to optimize its own state while also affecting the behavior of other agents. To enable adaptive decision-making, each workstation agent continuously monitors its availability, performance, and quality indicators. These OEE components produce local signals when deviations occur, enabling AMR agents to prioritize material deliveries or removal tasks accordingly. This way, OEE becomes an operational control input rather than a retrospective KPI. The implementation of this mechanism and its use within the simulation and optimization workflow are described below. A detailed comparison between virtual factory outputs, production-order feedback, and real-time DIMUSA measurements is presented in Section 3.6, where the performance of the proposed control model is evaluated under real industrial conditions.

AMR Mission Generation and Optimization

In addition to workstation-level OEE monitoring, the system includes a mechanism that enables AMR agents to generate and optimize missions. Each mission is defined as a sequence of pick-up and delivery tasks, determined by real-time workstation requests and buffer status. The mission generation process relies on two levels of decision-making. At the upper level, the system selects which nodes (loading/unloading points) to visit in the next mission based on urgency signals, such as material shortages or buffer congestion.

At the lower level, the system computes the optimal path through these nodes, ensuring that the AMR follows the most efficient route while meeting the time constraints and resource priorities.

Figure 12 illustrates the AMR-based logistics control system, showing how robot control modules, AI-based path optimization, ERP integration, and efficiency analysis are connected to OEE-driven decision-making.

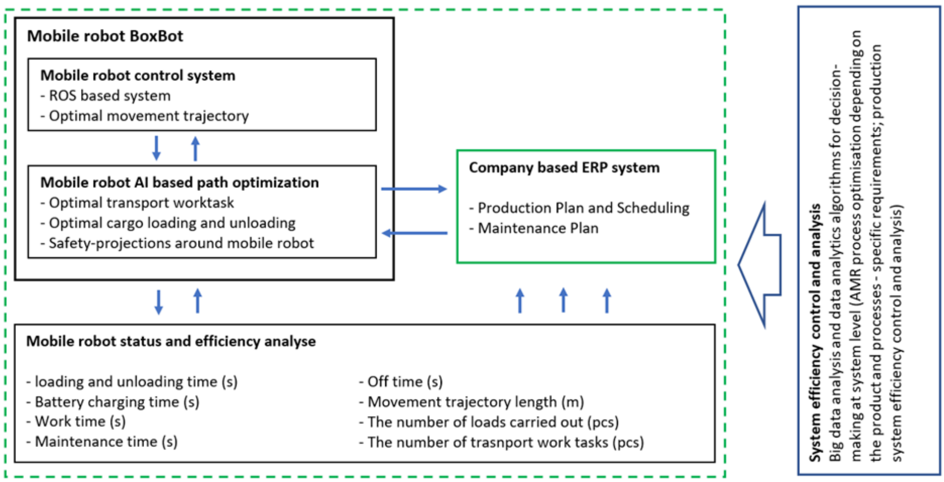


Figure 12. Architecture of the AMR-based logistics control system, integrating robot control, AI-based path optimization, ERP connectivity, and performance analysis (adapted from Publication IV).

The optimization model is represented as a directed graph, where each node corresponds to a workstation, buffer, or auxiliary area (e.g., a washing or maintenance area). Edges between nodes are weighted by distance or estimated travel time, updated dynamically from sensor data. This representation allows missions to be adapted online to reflect real factory conditions (Case B - Food industry).

For path optimization, several algorithms were tested, including genetic algorithms (GA), ant colony optimization (ACO), and classical shortest-path methods such as Dijkstra's algorithm. While evolutionary algorithms provided flexibility for complex layouts, Dijkstra's method proved most effective for fast recalculation in dynamic environments, as demonstrated in Case B - Food industry. Figure 13 presents the AMR motion model, represented as a directed graph of nodes and edges, where each node corresponds to a loading, unloading, or maintenance point.

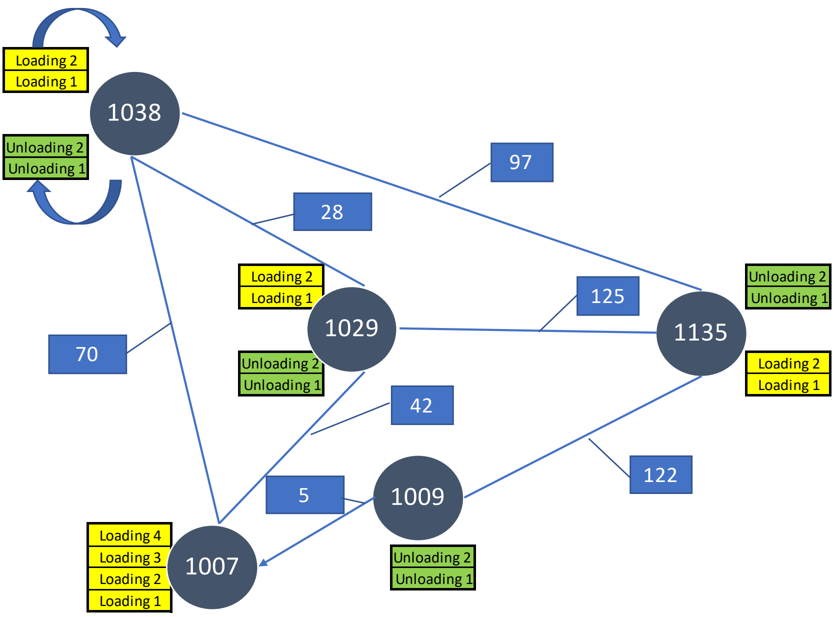


Figure 13. AMR optimization model represented as a directed graph, where nodes correspond to loading/unloading points and edges are weighted by distance or travel time (adapted from Publications IV and VI).

Once the mission nodes were defined in the motion model, the next step was to compute the optimal path for the AMR. The optimization considered factors such as distance, estimated travel time, and workload priorities, ensuring that each route minimized idle times while meeting workstation demands. This step translated the abstract graph-based representation into a practical navigation plan for the robot, balancing efficiency and real-time adaptability. Figure 14 illustrates the result of optimal path generation for one mission, showing how the selected route passes through required nodes in the most efficient sequence.

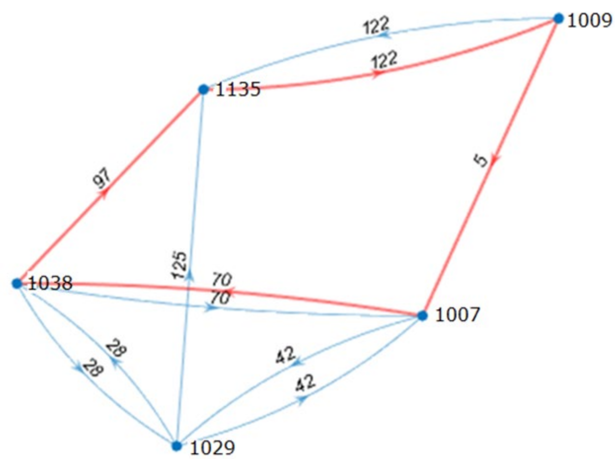


Figure 14. Example of optimal AMR path (red line) generation, showing the most efficient route through selected nodes based on real-time mission priorities (adapted from Publications IV and VI).

This optimization logic is detailed in Publication IV.

Clustering Analysis

To identify systemic inefficiencies that extend beyond individual workstations, clustering techniques were applied to OEE-based datasets in both simulation and real industrial environments.

In Case D – Wood industry, a virtual factory model was created in Siemens Plant Simulation, and workstation-level OEE metrics were analyzed over 3 months. A k-means clustering algorithm (k = 5, using the elbow method) was applied to segment workstations based on performance patterns. This allowed the identification of the five most efficient and five least efficient workstations, providing targeted insights for layout redesign, buffer sizing, and flow balancing. The analysis demonstrated how clustering could be used proactively during the design stage to prevent bottlenecks before implementation in a physical facility.

In Case E – Apparel industry, clustering was applied to real-time production data streams structured via the DIMUSA platform, allowing continuous analysis of workstation behavior within a digital shadow environment. A two-step approach was used: first, DBSCAN filtering removed outliers and anomalous data points, such as excessively long idle times; then, k-means clustering classified operational states into interpretable groups (e.g., “stable,” “delayed,” “high variation”). This workflow enabled supervisors to visualize recurring inefficiencies, especially those related to micro-batch sequencing and workstation synchronization, and to cross-validate them against simulation scenarios.

These provided supervisors with clear, understandable insights into performance disparities, helping to prioritize interventions such as operator reallocation, buffer resizing, or maintenance-related actions based on emerging performance data anomalies.

Figure 15 illustrates the results of clustering OEE metrics, grouping workstations by availability and performance levels (Case D – Wood industry). Critical bottlenecks can be identified in the lower-left quadrant (low availability, low performance), while benchmarks for efficiency are found in the upper-right quadrant (high availability, high performance).

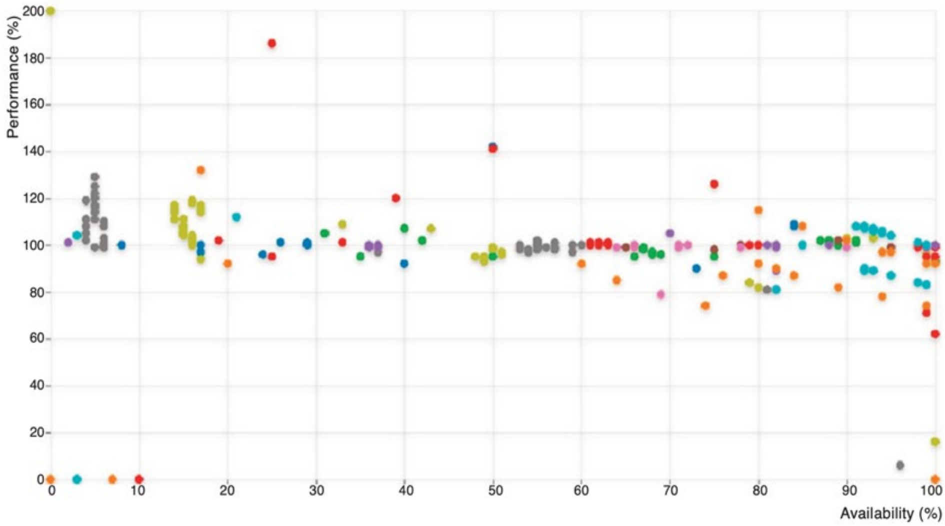


Figure 15. Clustering of workstation OEE data by availability and performance, identifying efficiency benchmarks and bottleneck-prone stations (adapted from Publications VII).

Integration into Control Flow

In the decentralized control framework, two complementary mechanisms are combined: the AMR-based transport system and OEE-based performance monitoring with clustering analysis.

On the operational side, the AMR agents ensure that workstations are consistently supplied with raw materials and that finished products are transported to the next designated buffer or workstation. Each mission originates directly from the shop floor: when a workstation agent signals a shortage, the AMR delivers the necessary input materials; when a buffer agent indicates that output is ready for removal, the AMR clears the workstation. In addition, the AMR system is connected to higher-level planning tools, including the ERP system and the DIMUSA platform, which provide production plans, task priorities, and workstation norms. This integration aligns local AMR decisions with global production objectives, ensuring that logistics respond promptly to real-time shop floor needs while maintaining consistency with overall schedules. The underlying architecture for AMR control, including robot navigation, AI-based optimization, and ERP connectivity, was detailed and validated in earlier work (Case B – Food industry).

On the analytical side, OEE monitoring and clustering provide diagnostic feedback on workstation efficiency. While AMRs ensure the physical flow of materials, OEE indicators reveal whether workstations are operating effectively or experiencing losses due to issues with availability, performance, or quality. Clustering analysis extends this perspective by uncovering patterns across multiple workstations: identifying bottleneck-prone cells, recurring inefficiencies, and underutilized resources. These insights do not directly control AMR behavior but instead guide supervisors and engineers in prioritizing improvement actions, refining layouts, or reallocating resources. Such applications were demonstrated in the wood industry case, where k-means clustering was applied to workstation OEE metrics (Case D – Wood industry), and in the apparel SME case, where a combination of DBSCAN and k-means clustering in the DIMUSA platform revealed systemic inefficiencies (Case E – Apparel industry).

Together, these two layers provide a balanced integration: AMRs secure short-term adaptability by responding to local signals, while ERP/DIMUSA plans, and OEE clustering support long-term system improvements by highlighting inefficiencies that require strategic attention. This dual perspective—operational execution complemented by analytical feedback—was validated across multiple case studies and resulted in smoother synchronization between workstations and logistics, reduced idle time, and improved throughput without relying on centralized scheduling. By embedding both reactivity and adaptability into the control loop, the framework aligns directly with Industry 5.0's goals, emphasizing autonomy, resilience, and human-centric decision support.

3.5 Overview of Industrial Cases

To ensure both generalizability and practical relevance, the research was validated through **five industrial case studies conducted in collaboration with manufacturing companies across sectors.** Each case was carefully selected to represent a distinct combination of product types, workflow characteristics, logistics requirements, and levels of automation maturity. The intention was not only to test the decentralized control model in a narrow context but also to examine its adaptability across heterogeneous environments, ranging from process-intensive industries to high-variability SMEs. In this chapter, the overview also explains the origins of the empirical data used for modeling, simulation, and validation across these cases. In the following subchapters, each use case is presented with a consistent structure—Problem, Applied Technology, and Contribution—to clearly show both the initial challenge and the specific role of the methods and tools used in the research.

Case A – Chemical industry (Publication I, III)

The chemical industry served as the starting point for validating the methodology, as it provided a structured production environment with well-defined flows and a strong demand for reliable data acquisition. This context enables testing the feasibility of the Virtual Factory approach, in which data integration, sensor placement, and intralogistics processes could be evaluated in a digital environment before implementation in the physical system.

Publication I introduced the Virtual Factory framework for the chemical industry, focusing on real-time data acquisition and sensor integration. The model demonstrated how IR, RFID, and weight sensors could be positioned to monitor AMR activity, loading platforms, and conveyor flows. This enabled the systematic evaluation of sensor roles in logistics coordination, ensuring that real-time signals could later be utilized as inputs for OEE monitoring and informed decision-making. Publication III further extended this approach by applying the Virtual Factory to intralogistics analysis in the same industrial context. Here, 3D simulations were used to model production line operations, material handling flows, and alternative layout configurations. These studies confirmed that the Virtual Factory not only supported sensor-strategy validation but also served as a decision-support tool for optimizing production logistics in process-intensive industries.
Focus: Real-time data acquisition, sensor integration, and intralogistics simulation in the chemical industry.
Contribution: Development of a Virtual Factory framework that enabled sensor placement validation and logistics flow analysis, combining simulation-based planning (Publication I) with intralogistics scenario evaluation (Publication III).

Figure 16 presents the sensor placement diagram showing how IR, RFID, and weight sensors were integrated with AMR and conveyor systems to support real-time data collection. Figure 17 shows the physical implementation of RFID and optical sensors in the production environment, enabling automatic identification and synchronization of transport tasks with AMRs.

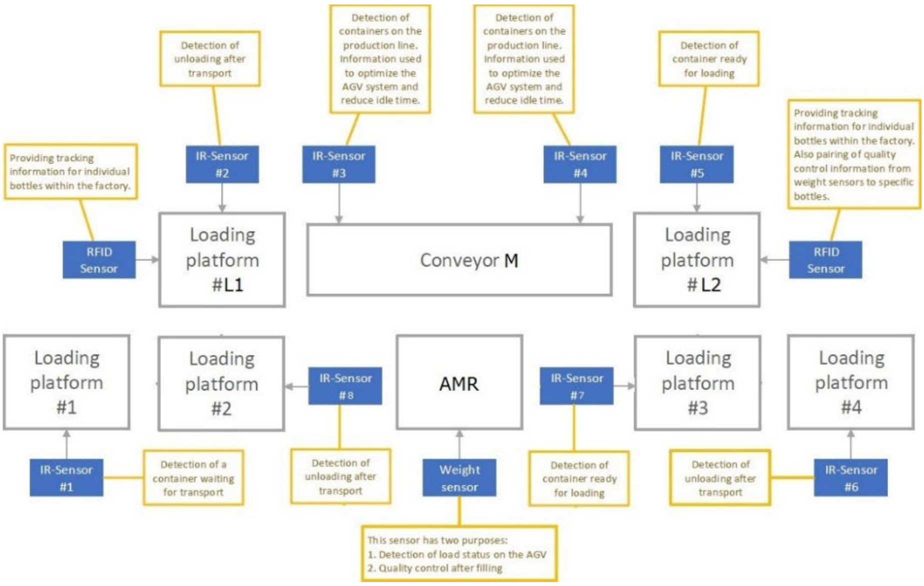


Figure 16. Virtual Factory sensor placement diagram for the chemical industry case, showing the integration of IR, RFID, and weight sensors with AMR and conveyor systems to support real-time data acquisition (adapted from Publication I).

Figure 17. Implementation of RFID and optical sensors in the chemical industry case, enabling automatic identification and synchronization of transport tasks with AMRs (adapted from Publication I).

Case B – Food industry (Publications II, IV, VI)

The food industry represented a domain where intralogistics plays a critical role in throughput and efficiency, making it an ideal environment for evaluating AMR coordination and AI-based decision support. Frequent material movements, variable product flows, and strict hygiene requirements posed a realistic challenge for the decentralized model.

Focus: Simulation-based intralogistics analysis with AMRs, KPI evaluation, and clustering of workstation performance.

Contribution: Provided OEE-based workstation modeling, 3D simulation of logistics flows, and tested AI-enhanced AMR coordination.

Figure 18 illustrates a logistics simulation scenario developed for the food industry case, where AMRs were tested under varying load conditions. The simulation environment enabled the evaluation of task allocation strategies, validation of AMR responsiveness, and identification of potential bottlenecks in intralogistics. By adjusting workload intensity and transport frequency, the model revealed that decentralized decision-making improved throughput time and reduced workstation idle time.

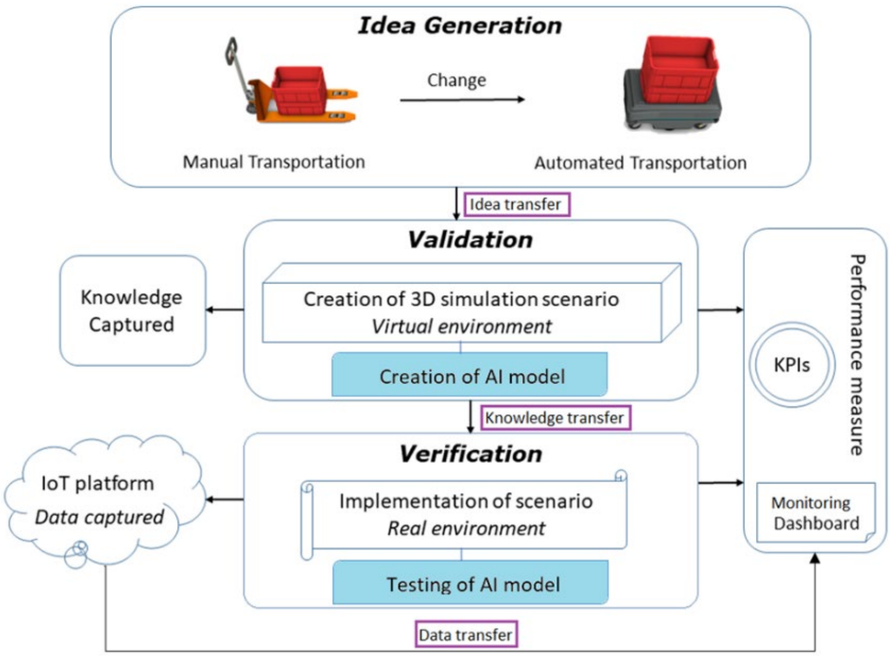


Figure 18. Proposed approach for analyzing the performance of AMRs in production logistics, integrating simulation, AI-based task allocation, and KPI monitoring (adapted from Publication VI).

Figure 19 presents the AMR loading and unloading station model that was implemented to represent critical material transfer points in the food industry. This model served as a basis for analyzing the interactions among AMRs, conveyors, and buffer areas, and helped quantify the effects of automated transport on OEE. Figure 19 illustrates the arrangement of different buffer areas along the AMR transport paths, including the empty boxes area (W), filled boxes area (F), dirty boxes area (D), and process buffers for picking up and placing goods. The unified view shows the loading and unloading locations utilized by AMRs for material handling within the production environment. The combination of Figure 18 and Figure 19 demonstrates how simulation-driven analysis supports the validation of AI-enhanced intralogistics coordination in environments with high product variability and strict operational constraints.

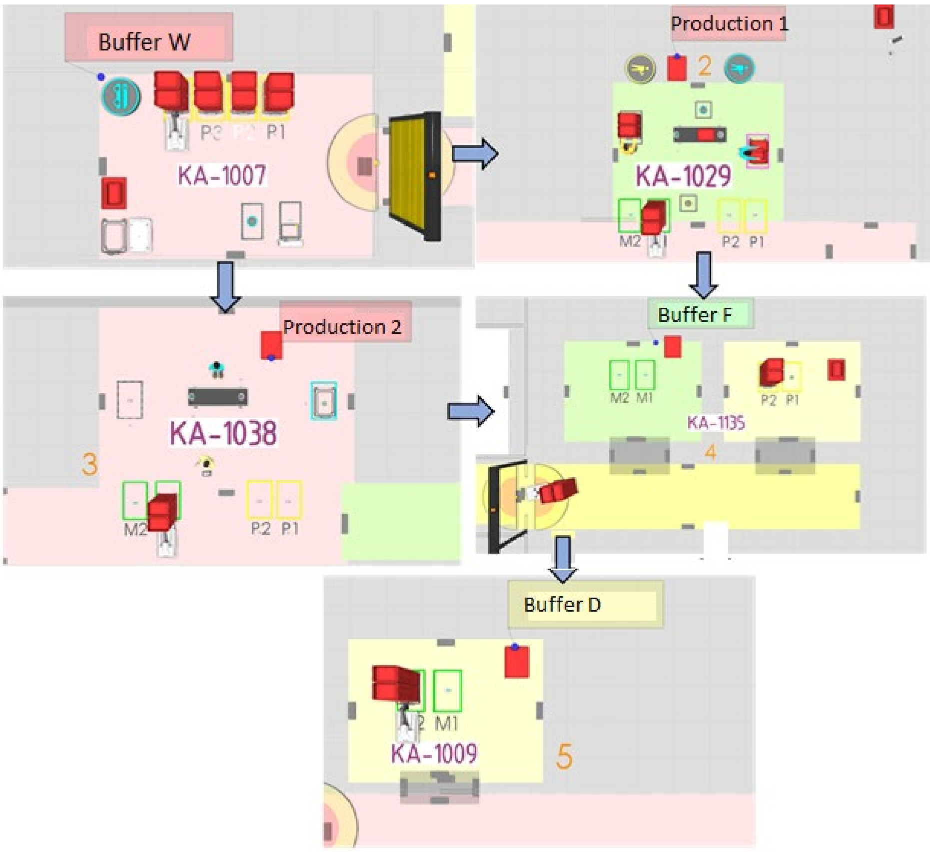


Figure 19. AMR loading and unloading station model in the food industry case (adapted from Publication IV).

Case C – Metal industry (Publication V)

The metal industry case was used to validate the methodology in a discrete manufacturing environment, where production data were often fragmented and heterogeneous, and were generated under highly variable operating conditions. This case highlighted the practical challenges of acquiring, preprocessing, and visualizing shop floor data as a reliable basis for advanced analytics.

Focus: Establishing methods for industrial data acquisition and visualization at the workstation level, enabling consistent and interpretable inputs for AI-based optimization.

Contribution: The study demonstrated how to systematically collect, structure, and integrate machine logs, downtime records, and sensor readings from different workstations into dashboards. These visualizations provided both operators and engineers with clear insights into workstation behavior while ensuring that subsequent AI applications (e.g., OEE monitoring, decision-support models) were based on accurate, consistent data. Figure 20 presents the robotic bending workstation model, which illustrates the integration of a Yaskawa robot with a sheet-metal bending machine and associated material-handling stations. This model served as a reference for capturing operational data and testing the feasibility of implementing a digital twin in a metal industry environment.

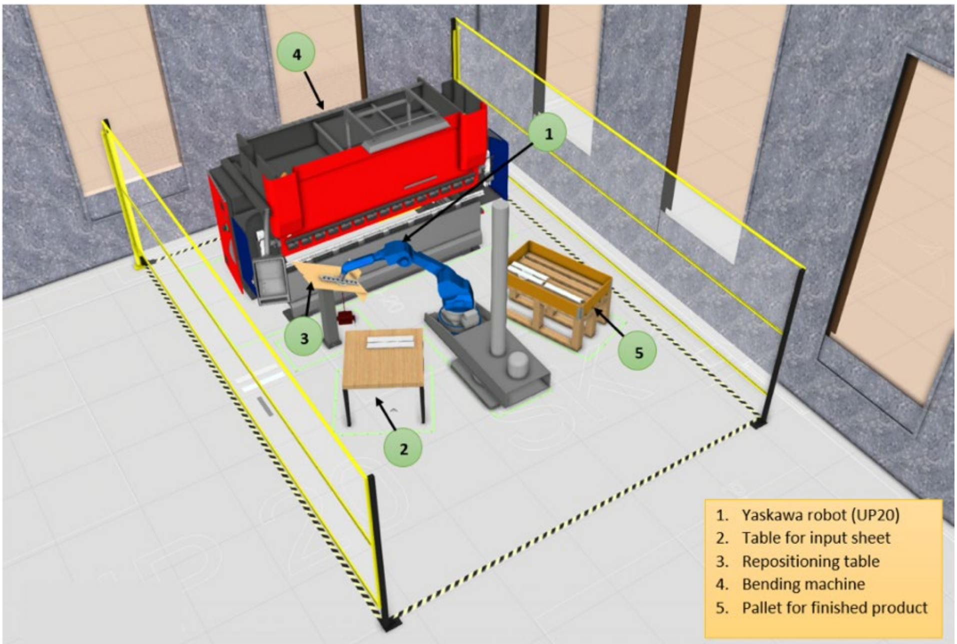


Figure 20. Robotic bending workstation model in the metal industry case, showing the integration of a Yaskawa robot with a bending machine, input/output tables, and palletizing stations (adapted from Publication V).

Figure 21 shows the DIMUSA dashboard view, where real production data from both the bending machine and robotic workstation were collected and visualized across a single shift. Together, the figures demonstrate the complementary role of digital twin modeling and data analytics in creating a transparent, data-driven decision-support framework.

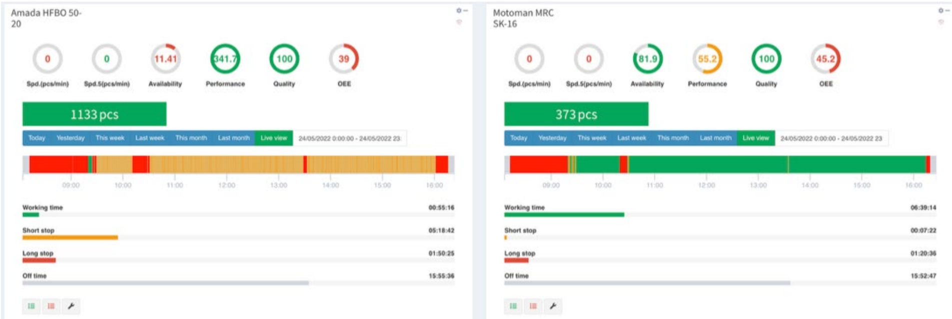


Figure 21. DIMUSA dashboard view from the metal industry case, visualizing bending machine and robotic workstation data collected during one production shift (adapted from Publication V).

Case D – Wood industry (Publication VII)

The wood industry case provided a context characterized by batch-based variability, long material flows, and frequent changes in product types. This created an ideal environment for extending the digital twin methodology by integrating simulation with AI-based analysis. The case demonstrated how a virtual factory model could be used to represent complex layouts and evaluate the impact of reconfiguration on throughput and workstation performance.

Focus: Development of a virtual factory model enhanced with AI-based clustering for OEE optimization in a batch-production environment.

Contribution: The study demonstrated how Siemens Tecnomatix Plant Simulation can be integrated with OEE-driven analysis to optimize resource allocation and minimize bottlenecks in multi-stage processes. Clustering methods were applied to workstation-level OEE data, providing actionable insights for rebalancing production flows and improving system utilization. The integration of these techniques validated the scalability of the decentralized model to production systems with high variability and long cycle times. Figure 22 illustrates the virtual factory model developed for the wood industry case, implemented in Siemens Plant Simulation. The model enabled evaluation of resource utilization, material flow, and production layout efficiency. Resource statistics were used to identify bottlenecks and idle times, supporting data-driven decisions for logistics and production optimization.

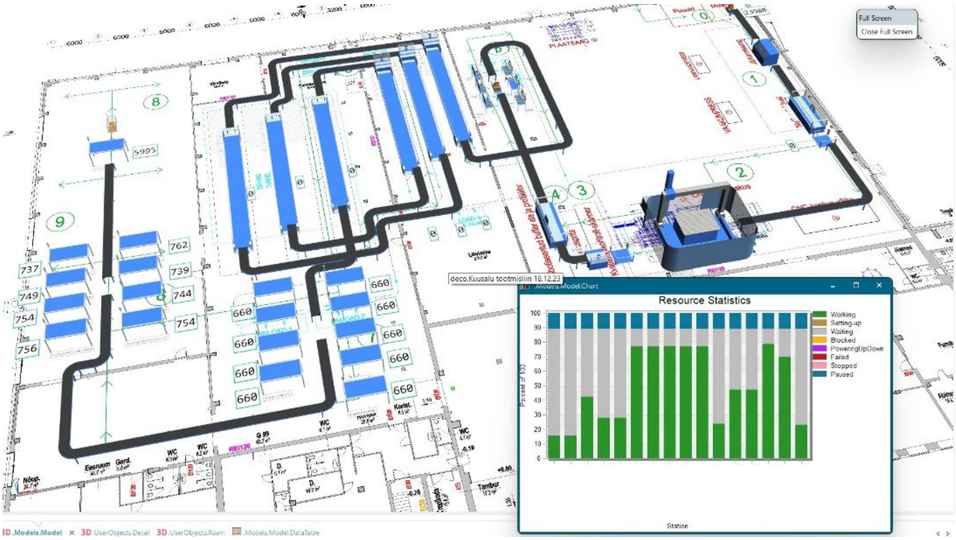


Figure 22. Virtual factory model of a wood industry production line in Siemens Plant Simulation, including resource statistics used for analyzing workstation utilization and bottlenecks (adapted from Publication VII).

Case E – Apparel industry (Publication VIII)

The apparel industry case was selected as a particularly demanding validation for the decentralized model, owing to the high variability of customized products, frequent changeovers, and limited resources typical of SMEs. This environment provided an opportunity to test whether the proposed approach could remain scalable and interpretable under conditions where flexibility and rapid adaptation are crucial.
Focus: Implementation of an AI-driven digital twin for production logistics optimization in a custom sportswear SME.
Contribution: The case demonstrated the development and deployment of the DIMUSA system, which integrated digital twin modeling, clustering analysis, and AI-based logistics decision support. Real-time workstation-level data were collected and visualized in dashboards, while clustering algorithms (K-means combined with DBSCAN) were used to detect anomalies and recurring inefficiencies. Simulation models were employed to validate improvement scenarios and to cross-check analytical insights with real-world observations. The results confirmed that even a lightweight, modular digital twin system can enhance transparency, provide interpretable feedback for operators, and support continuous improvement in SMEs with limited digital infrastructure.

To provide context for the pilot implementation, Figure 23 presents the digital twin layout of the apparel factory used in the case study. The model illustrates the shop floor configuration, including workstations, material buffers, and AMR transport routes, which were digitally replicated to capture the dynamics of production flow. This visualization was essential for planning the data acquisition strategy and for designing clustering-based performance analysis. By mapping the genuine factory into a virtual environment, the research ensured that subsequent DIMUSA implementation and anomaly detection could be directly validated against actual production conditions.

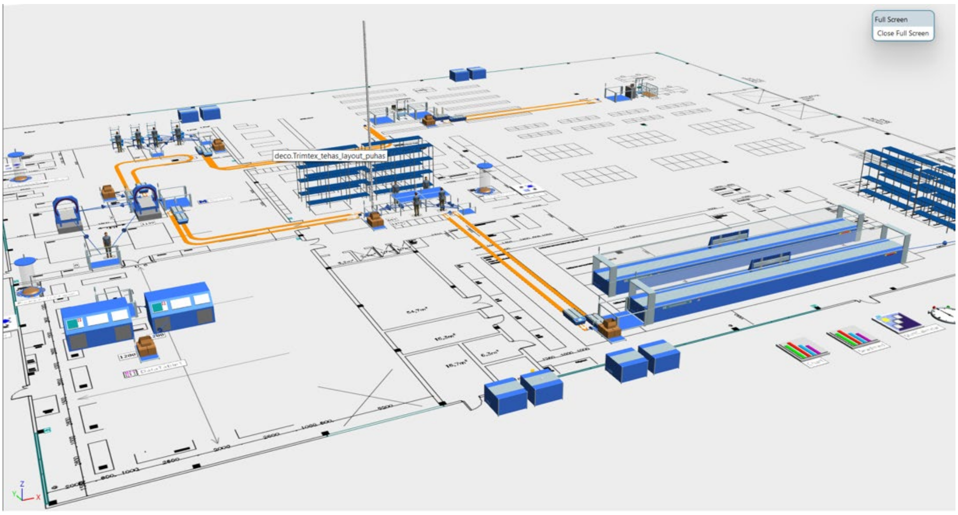


Figure 23. Digital twin layout of the apparel factory in the SME case, illustrating workstation configuration, material buffers, and AMR transport routes (adapted from Publication VIII).

One of the central findings was the discrepancy between simulation assumptions and actual production behavior. Figure 24 illustrates this by comparing workstation availability values generated in the virtual factory model (a) with actual measurements collected via DIMUSA sensors (b). The contrast highlights how simulation tends to assume more stable availability patterns, whereas real-world SME operations exhibit greater fluctuation due to manual handling, operator-induced variability, and micro-batch sequencing dependencies. By visualizing these differences, the system provided decision-makers with actionable insights into synchronization problems, material readiness delays, and operator coordination issues, which would have been difficult to detect with standard KPI reporting alone.

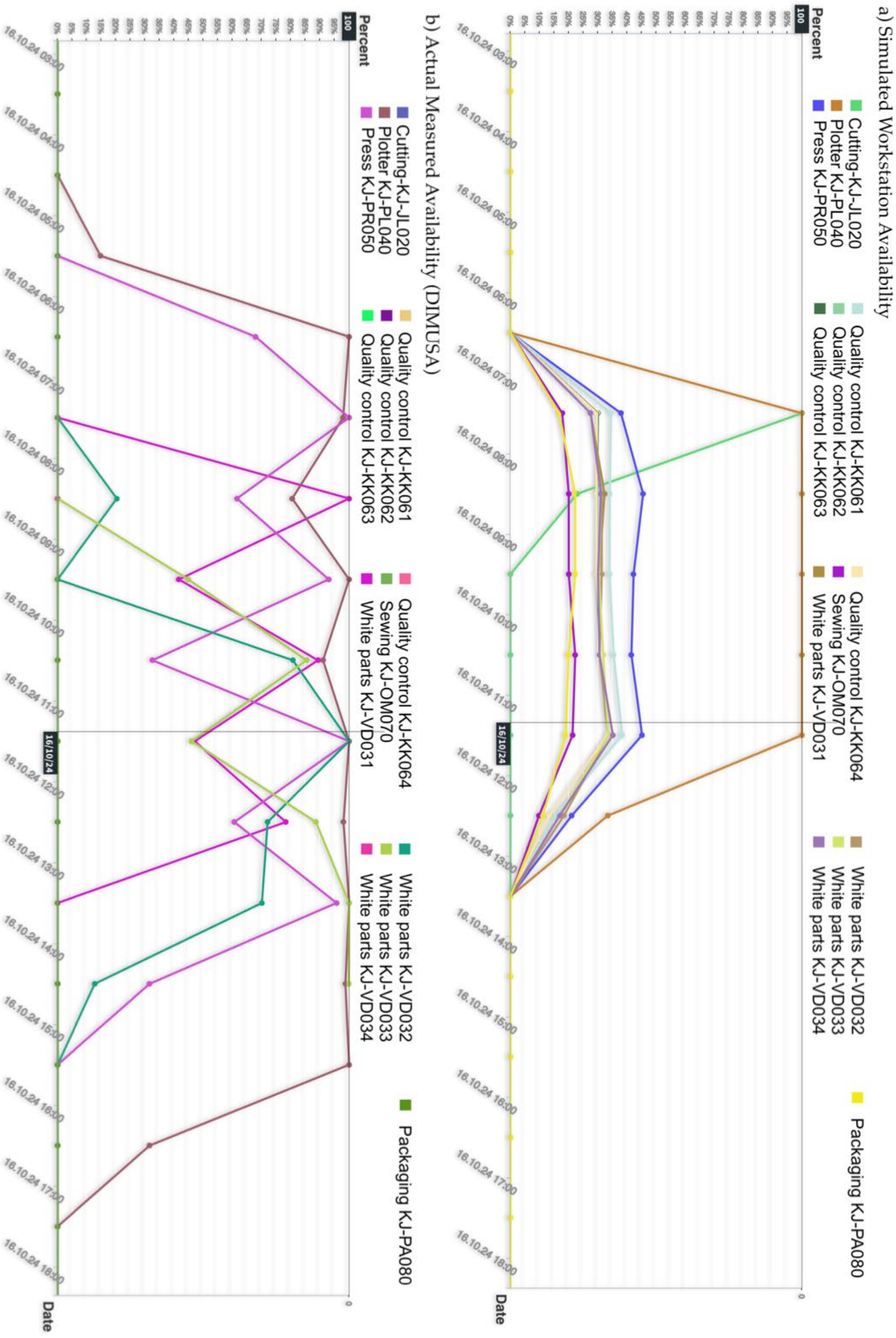


Figure 24. Comparison of workstation availability in the apparel SME case: (a) simulation model assumptions vs. (b) actual DIMUSA measurements collected on 16 October 2024 (adapted from Publication VIII).

Empirical Contributions

The following section outlines the empirical foundation of this research by summarizing the industrial case studies, data sources, and observed operational challenges that informed the development of the proposed digital optimization and control model. Rather than presenting conclusions, this overview introduces the practical contexts in which the methodology and technologies were applied. A detailed analysis of the empirical results and their implications is provided later in the Discussion chapter.

Together, the five case studies provided a comprehensive and robust empirical foundation for the dissertation. By spanning industries as diverse as chemicals, food, metals, wood, and apparel, they demonstrated that the proposed decentralized control system is not limited to a single production type but can be transferred across heterogeneous contexts. Each case contributed distinct insights: the chemical industry case highlighted the importance of structured data acquisition and sensor integration; the food industry emphasized the role of AMRs and intralogistics coordination; the metal industry provided validation for OEE clustering and data-driven optimization; the wood industry tested the scalability of virtual factory models in batch production; and the apparel industry case proved the feasibility of full digital twin implementation in a high-variability SME setting.

These cases collectively validated the modularity and scalability of the decentralized architecture. In practice, this meant that new agents could be added without redesigning the entire system, and that the same core logic functioned effectively in both highly automated and resource-constrained environments. The diversity of contexts also ensured that the proposed solution was stress-tested across very different organizational and technical conditions, including centralized ERP environments, hybrid manual-automated workflows, and SME-specific constraints such as limited IT infrastructure.

The case studies further enabled the testing of autonomous control algorithms under realistic conditions. Scenarios such as high-load AMR utilization, workstation bottlenecks, buffer congestion, and equipment failures were addressed not only in simulation but also in live production trials. The results confirmed that the system could dynamically reprioritize tasks, rebalance workloads, and recover from disturbances without central supervision, demonstrating robustness and adaptability in environments characterized by uncertainty.

From a performance perspective, the validation showed measurable improvements. Across different industries, workstation availability increased due to reduced waiting times, throughput time was shortened thanks to synchronized logistics, and OEE scores improved as a result of combined gains in availability, performance, and quality. In some cases, additional benefits such as higher AMR utilization and reduced operator workload were observed, further strengthening the business case for decentralized logistics control.

Ultimately, this cross-sector validation confirmed the model’s generalizability. It showed that decentralized, AI-enhanced agents are not only theoretically viable but also practically deployable across multiple industries. This scalability positions the proposed solution as a strong candidate for Industry 5.0 applications, where resilience, adaptability, and human-centric decision support are increasingly required.

3.6 Validation and Performance Indicators

To evaluate the performance, scalability, and robustness of the proposed decentralized production control system, a comprehensive simulation environment was developed and iteratively refined. This environment replicated real production layouts, workflows, and logistics interactions by integrating digital twins with agent-based control logic. It enabled systematic testing under representative operating conditions, while also allowing the exploration of edge-case scenarios—such as AMR congestion, workstation breakdowns, or highly variable task sequences —that would be difficult, costly, or risky to reproduce in physical factories. By combining realism with experimental flexibility, the simulation framework provided a safe yet reliable foundation for validating the decentralized architecture before industrial piloting (Case B – Food industry and Case D – Wood industry).

Validation Approach

The validation of the proposed decentralized control model follows a layered strategy that combines virtual-factory simulations, production-order feedback, and real-time sensor measurements. This structure allows the model to be evaluated under both idealized and real operating conditions. Virtual factory simulations provide upper-bound performance baselines; production records offer historical references of expected behaviour; and DIMUSA real-time data expose the true variability of the shop floor, including micro-stoppages, operator-induced delays, and transport disruptions. By integrating these complementary data sources, the validation process captures the gap between planned, simulated, and actual performance. The following subsections present the results of this multi-layered validation in detail.

Virtual Factory Baseline (Case E – Apparel industry)

To evaluate how workstations should perform under ideal conditions, a virtual factory model was created for Case E. The model offers an optimal performance baseline, while actual monitoring reflects variability caused by manual handling, operator decisions, and small-batch sequencing. Table 7 displays workstation-level OEE results produced by the virtual factory model.

Table 7. Workstation-level OEE values from the virtual factory model in Case E – Apparel industry (Publication VIII).

Date	Workstation	Availability %	Performans %	Quality %	OEE %	TEEP %	Result/pcs
2024/10	Plotter KJ-PL040	67%	100%	100%	67%	16%	9200
2024/10	Press KJ-PR050	29%	100%	100%	29%	7%	9200
2024/10	Quality control KJ-KK061	24%	100%	100%	24%	6%	2300
2024/10	White parts KJ-VD031	22%	101%	100%	22%	5%	2622
2024/10	White parts KJ-VD032	22%	101%	100%	22%	5%	2622
2024/10	White parts KJ-VD033	21%	101%	100%	22%	5%	2599
2024/10	White parts KJ-VD034	21%	101%	100%	22%	5%	2599
2024/10	Quality control KJ-KK062	21%	100%	100%	21%	5%	2300
2024/10	Quality control KJ-KK063	21%	100%	100%	21%	5%	2300
2024/10	Quality control KJ-KK064	21%	100%	100%	21%	5%	2300
2024/10	Cutting KJ-JL020	15%	100%	100%	15%	4%	20355
2024/10	Sewing KJ-OM070	14%	100%	100%	14%	3%	9200
2024/10	Packaging KJ-PA080	14%	100%	100%	14%	3%	9200

In this simulated environment, availability, performance, and quality metrics were calculated assuming stable process conditions, synchronized material flow, and minimal human-related disruptions. Transport tasks are completed on schedule, cycle times stay consistent, and operator influence is minimal. This model, therefore, represents the “ideal state” of the apparel production system.

The benefit of using a virtual factory baseline is that it enables performance benchmarking and scenario testing prior to industrial deployment. However, virtual models tend to overestimate efficiency, especially workstation availability, because they do not account for short interruptions, micro-delays, or operator-driven disturbances.

Comparison with Real-Time DIMUSA Measurements

To address these limitations, Table 8 provides a detailed comparative analysis of two representative workstations (Plotter and Press) based on three complementary data sources:

- production order feedback (manual input),
- virtual factory simulation outputs,
- real-time DIMUSA measurements.

Table 8. Comparative analysis of workstation-level performance based on production order feedback, virtual factory model outputs, and real-time DIMUSA measurements in Case E – Apparel industry (Publication VIII).

Plotter KJ-PL040

Actual execution of work orders (manual input)

Code	Workstation	Actual start	Actual stop	Off	Short stop	Long Stop	Working	Quantity/m2
Micro-batch-44-025-CAA	Plotter KJ-PL040	16/10/2024 5:56:02	16/10/2024 7:31:21	00:00:00	00:01:12	00:00:00	01:34:07	115.9 m2
Micro-batch-44-023-CA	Plotter KJ-PL040	16/10/2024 7:32:18	16/10/2024 8:31:58	00:00:00	00:01:02	00:03:23	00:55:14	73.88 m2
Micro-batch-44-034-CAA	Plotter KJ-PL040	16/10/2024 14:33:11	16/10/2024 16:23:18	00:00:00	00:00:00	00:05:04	01:45:01	148.58 m2
Micro-batch-44-032-CM	Plotter KJ-PL040	16/10/2024 10:26:16	16/10/2024 12:36:55	00:00:00	00:01:08	00:00:20	02:09:09	164.1 m2
Micro-batch-44-028-CK	Plotter KJ-PL040	16/10/2024 8:52:37	16/10/2024 10:21:49	00:00:00	00:00:48	00:00:00	01:28:23	104.03 m2
Micro-batch-44-037-CM	Plotter KJ-PL040	16/10/2024 12:37:27	16/10/2024 14:32:58	00:00:00	00:00:44	00:00:00	01:54:46	169 m2
			TOTAL:	00:00:00	**0:04:55**	**0:08:49**	**9:46:43**	**775.49 m2**

Virtual factory simulation data

Shift	Workstation	Start	End	Off	Short stop	Long Stop	Working	Quantity/m2	Availability	Performance	OEE
17.10.2024	Plotter KJ-PL040	16/10/2024 7:00:00	16/10/2024 15:00:00	00:00:00	**00:00:01**	**02:39:59**	**05:20:00**	400	67%	100%	67%

DIMUSA real-time data

Shift	Workstation	Start	End	Off	Short stop	Long Stop	Working	Quantity/m2	Availability	Performance	OEE
17.10.2024	Plotter KJ-PL040	16/10/2024 6:00:00	16/10/2024 18:00:00	00:00:00	**00:04:55**	**01:56:13**	**09:58:51**	775	83%	0%	0%

Press KJ-PR050

Actual execution of work orders (manual input)

Code	Workstation	Actual start	Actual stop	Off	Short stop	Long Stop	Working	Quantity/m2
Micro-batch-44-025-CAA	Press KJ-PR050	17/10/2024 11:26:31	17/10/2024 12:08:10	00:00:00	00:00:00	00:00:00	00:41:38	115.9 m2
Micro-batch-44-023-CA	Press KJ-PR050	17/10/2024 12:09:23	17/10/2024 12:37:29	00:00:00	00:00:00	00:00:40	00:27:25	73.88 m2
Micro-batch-44-020-CAA	Press KJ-PR050	17/10/2024 8:34:12	17/10/2024 9:06:07	00:00:00	00:00:00	00:00:34	00:31:20	91.3 m2
Micro-batch-44-032-CM	Press KJ-PR050	17/10/2024 9:09:51	17/10/2024 10:05:54	00:00:00	00:00:28	00:00:00	00:55:34	164.1 m2
Micro-batch-44-037-CM	Press KJ-PR050	17/10/2024 13:00:30	17/10/2024 13:52:52	00:00:00	00:00:00	00:00:00	00:52:22	169 m2
			TOTAL:	00:00:00	**0:00:28**	**0:01:15**	**3:28:21**	**614 m2**

Virtual factory simulation data

Shift	Workstation	Start	End	Off	Short stop	Long Stop	Working	Quantity/m2	Availability	Performance	OEE
17.10.2024	Press KJ-PR050	17/10/2024 7:00:00	17/10/2024 15:00:00	00:00:00	00:00:00	05:40:00	02:20:00	400	29%	99.9%	29%

DIMUSA real-time data

Shift	Workstation	Start	End	Off	Short stop	Long Stop	Working	Quantity/m2	Availability	Performance	OEE
17.10.2024	Press KJ-PR050	17/10/2024 6:00:00	17/10/2024 18:00:00	00:00:00	00:04:05	05:15:24	06:40:30	614	56%	4%	2%

Production order data offer a high-level view of output and downtime but lack the resolution to detect micro-stops. The virtual factory model provides idealized results, assuming stable operations. Real-time DIMUSA monitoring shows actual shop-floor conditions, capturing disruptions such as material shortages, operator delays, and micro-batch effects.

The comparison demonstrates that:

- Production feedback underestimates inefficiencies,
- simulation overestimates stability,
- Real-time monitoring exposes full variability.

These insights emphasize the need to combine digital-twin simulations with sensor-based measurements to get accurate and useful performance evaluations.

Simulation Tools and KPI Architecture

The simulation platform was implemented using a combination of specialized factory modeling tools and custom-developed agent modules. Visual Components and Siemens Plant Simulation were utilized to develop 3D layouts and replicate process flows. Meanwhile, Python-based agent logic controls AMRs, buffers, and workstations in real-time (Publications IV, VI, VII). The platform incorporated OEE emulation and transport event logging, enabling direct linkage between agent decisions and measurable performance indicators. To ensure consistency in evaluation, a set of KPIs was defined based on the information in Table 9. These KPIs enabled systematic comparison between baseline (manual/centralized) and decentralized (AI-controlled) logistics coordination. The framework included workstation availability, throughput time, OEE components, and AMR utilization, providing both efficiency and resilience measures for validation.

Table 9. KPI framework for validating decentralized intralogistics coordination (adapted from Publication II).

KPI	Current Scenario (manual)	Virtual Scenario (automated)	Real Scenario (automated)	Estimated improvement
P1: Defects	Irregularities existed due to the messy corridors (routes) with random boxes (crates)	Irregularities did not exist as in the simulation the designated routes were clearly defined for robots	Irregularities were mitigated as the implementation of robots in a real environment leads to neat and clean routes.	10% reduction in existing transportation defects
P2: On-time delivery	Insufficient amount of boxes at the right time and at the right place. High waiting time at production lines	Simulation enables to plan the number of boxes at right time and place. For 12 hours simulation run with 3 robots, minor waiting time was overserved.	On-time deliveries of empty red boxes were improved as robots connected to the IoT platform, communication between them facilitate the availability of empty boxes at the right time and at the right place.	5% increase in on-time delivery
P3: Inventory turnover	Inadequate inventory turnover due to the lack of boxes. The throughput was 321 boxes per hour.	For an hour simulation run in the virtual setup of the same scale, throughput was 336 boxes.	Sensors data and controlled planning of robots enabled to improve inventory turnover.	5% increase in inventory turnover
P4: Labour Cost	Manual transportation incurs cost, when human labour realized fatigue due to repetitive activities.	Enables effective planning to allocate the workers and robots for the right and productive job.	The proper planned implementation of robots leads to a reduction in operating transportation costs. As the number of logistic workers decreased.	15% reduction in the labour cost

To ensure realism, industrial datasets from Case B (Food industry) and Case C (Metal industry) were integrated into the simulation environment.

These datasets included workstation cycle times, buffer capacities, and transport lead times, reflecting real production behavior and thereby strengthening the credibility and practical relevance of the results.

The digital twin models reproduced essential elements of factory operation, including the spatial layout of production cells, workstation operating cycles, and material flows coordinated by AMRs. Dynamic disturbances, such as delayed deliveries, AMR congestion, or temporary failures, were systematically introduced to test the system's resilience. This hybrid simulation environment combined industrial realism with experimental flexibility, providing a robust testbed for validating the decentralized control framework under both standard and extreme operating conditions.

Validation Scenarios

To systematically test the proposed control system, a set of validation scenarios was developed and applied in both simulation and industrial case studies. The validation combined virtual factory simulations, production order feedback, and real-time monitoring through the DIMUSA system to ensure that the decentralized model was robust under both controlled and real operating conditions.

1. **Baseline vs. AI-controlled operation:** Centralized/manual transport dispatching was compared with the decentralized agent-based model. Key metrics included workstation idle time, throughput time, OEE evolution, and AMR utilization. Results consistently showed that the decentralized approach reduced workstation idle periods and improved flow stability (Publications II, IV, VI). Simulation outputs at the system level provided an idealized performance baseline, while detailed comparisons against production feedback and DIMUSA data (Figure 24) confirmed that real-world variability was successfully addressed.
2. **High-density load conditions:** The system behavior was assessed under conditions of increased material flow and limited AMR availability. Simulation results demonstrated that decentralized agents dynamically reprioritized transport missions to mitigate congestion effects and sustain stable throughput under constrained conditions (Publication VI).
3. **Disturbance and constraint scenarios:** Disturbances such as limited AMR availability and temporary buffer saturation were introduced in simulation to examine system behavior under non-ideal conditions. The decentralized control logic dynamically reassigned transport tasks and adapted buffer interactions, reducing the impact of disturbances without reliance on centralized supervision (Publications IV, VI).
4. **Layout sensitivity analysis:** Using the virtual factory in the wood industry, the effects of workstation and buffer configurations on flow efficiency were examined. Clustering analysis of OEE data highlighted spatial inefficiencies and underutilized areas, providing insights for redesign and routing optimization (Publication VII).
5. **Cross-validation of simulation and real data:** A layered validation approach was employed to compare workstation-level OEE indicators derived from the virtual factory (Table 7) with production order feedback and DIMUSA sensor measurements (Table 8). The comparison showed that simulation-based models

offer valuable baseline estimates but tend to overestimate availability and performance by ignoring waiting times, operator-induced variability, and micro-batch sequencing effects. Real-time data uncovered these hidden inefficiencies and emphasized the limits of purely simulation-driven analysis. Together, these validation scenarios demonstrate that decentralized, real-time data–driven control is more effective at handling variability and disruptions than static simulation models alone.

Key Outcomes

Across the validation scenarios, the decentralized control system consistently showed measurable improvements in production logistics. In Publication II, the focus was on comparing manual transportation with automated AMR-based transportation (before integrating the AI functionality). As shown in Table 9, the automation scenario was estimated to reduce transportation defects by about 10%, improve on-time delivery by about 5%, increase inventory turnover by about 5%, and reduce labour costs by about 15%. This set the initial benchmark for potential advantages of adopting digital and autonomous coordination. These baseline effects of automation are explained in more detail in Section 4.2 and Publication II. In Publication VIII, validation was extended by combining virtual factory simulations with real production data. Table 7 presents results from the DIMUSA virtual model, assuming workstations operating at 100% performance. These results were then compared to real-time measurements from two selected workstations (Plotter and Press) in Table 8. The comparison revealed that simulations tend to overestimate stability, whereas real data exhibited greater variability due to operator behavior, micro-stoppages, and manual interventions. A detailed explanation of this comparison and its implications is provided in Section 4.3 and Publication VIII. However, the actual measurements revealed idle time patterns and throughput losses that were not captured by simulation alone, thereby supporting the model's relevance and applicability in SMEs conditions.

It is important to note that the direct implementation of AI-generated recommendations into production processes has not yet been tested in Publication VIII. This highlights a clear direction for future research: the next step will be to assess how AI-driven decision support can further improve logistics coordination beyond baseline automation results (discussed in Chapter 5).

Overall, these findings confirm that the proposed decentralized system is both feasible and scalable. By integrating real-time OEE monitoring, agent-based AMR mission generation, and clustering-based performance analysis, the framework demonstrated measurable improvements in efficiency and resilience compared to manual or centrally coordinated approaches. These outcomes are discussed in detail in Chapters 4.2–4.5, where each validation scenario and industrial case is linked back to the decentralized control model.

4 Discussion and Synthesis

This chapter integrates the findings from the eight scientific publications and presents a unified analysis of the decentralized optimization model developed. While individual studies explored various aspects, including simulation, real-time feedback, AI-based control, and industrial implementation, this section brings them together to address the research problem holistically.

The synthesis focuses on identifying common threads and evaluating how the proposed model aligns with the goals of Industry 5.0, specifically in terms of novelty, including adaptability, human-centric design, and intelligent automation. Insights gained from simulation environments and industrial case studies are used to refine the conceptual model and validate its applicability in real-world production systems.

This chapter is structured into five main parts, covering a cross-publication analysis, the integration of digital twin and AI technologies, key lessons learned from the case studies, the final version of the proposed model, and the identified limitations and open research challenges. Together, these discussions provide the analytical foundation for the thesis, demonstrating how the developed model advances intelligent manufacturing systems.

4.1 Cross-Publication Analysis

The eight publications forming the foundation of this dissertation address the central research question from complementary technical and industrial perspectives.
Together, they demonstrate how a decentralized, AI-driven control and optimization model can be designed, simulated, and validated across multiple industrial contexts.
The contributions are grouped into three thematic clusters, summarized in Table 10.

The first cluster, represented by Publications I and VI, established the system's architectural and conceptual foundations. These studies define the layered control model and introduce the digital twin infrastructure as a framework for decentralized decision-making and feedback integration.

The second cluster (Publications II–V) concentrates on simulation-based design and optimization, where workstation agents, AMR agents, and buffer agents—along with their OEE-based decision signals—are used in controlled simulation environments. These studies confirmed the functional feasibility of the proposed model and its ability to adapt to dynamic production conditions.

The third cluster, consisting of (Publications VII and VIII), presents the industrial validation by applying the model in the wood and apparel industries. The results confirm the model's scalability, adaptability, and efficiency improvements in real production settings, thereby demonstrating its practical applicability. Across all clusters, the studies converge on shared principles: **agent-based autonomy, real-time feedback** loops, and the **integration of digital twins and AI** to enhance transparency and responsiveness. Together, these publications form a coherent progression from conceptual formulation to simulation testing and industrial validation, thus reinforcing the scientific and practical foundation of the thesis.

Table 10. Thematic clusters of publications and their main contributions.

Thematic cluster	**Publications**	**Main contribution**
Conceptual and system architecture foundations	I, VI	Defined the decentralized architecture and digital twin infrastructure; established the layered control model as a blueprint for agent-based optimization.
Simulation-based design and optimization	II, III, IV, V	Developed and tested intralogistics coordination models with AMRs; validated agent logic using OEE, idle time, and transport delays under controlled simulation environments.
Industrial application and validation	VII, VIII	Applied the model in the wood and apparel industries; demonstrated scalability, adaptability, and measurable efficiency gains in real production settings.

Across the eight publications, the research questions, industrial use cases, and methodological foundations are covered in a complementary way. Publications I and VI provide the conceptual and system-architecture foundations supporting RQ1 and RQ3. Publications II–V primarily address RQ1–RQ3 through simulation-based design, AMR coordination, and OEE-driven performance analysis in the food, chemical, and metal industry cases. Publications VII and VIII address RQ2–RQ4 through industry validation in the wood and apparel sectors, demonstrating alignment with Lean and DMAIC principles as well as Industry 5.0 goals such as human-centricity, transparency, and resilience. The alignment between research tasks, research questions, and publications is summarized in Table 1 for clarity. Together, these studies form a clear progression from theoretical basis to simulation testing and real-world application.

4.2 Integration of Digital Twin and AI-Driven Control

The integration of digital twins and artificial intelligence (AI) is a core innovation of this dissertation. Together, these technologies enable a decentralized production control model that is adaptive, self-regulating, and aligned with Industry 5.0's guiding principles. This integration builds on the digital twin architecture introduced in Section 3.2 and the AMR decision logic developed in Section 3.4 and corresponds to the overall system architecture illustrated in Figure 10.

The digital twin functions as a dynamic, real-time virtual representation of the physical production system. It mirrors the state of workstations, buffers, AMRs, and material flows, and incorporates production orders and inventory levels. Beyond serving as a simulation sandbox for testing alternative logistics scenarios, the twin continuously synchronizes virtual planning with physical execution. Publications I, VI, and VII developed and validated digital twin environments using platforms such as Siemens Plant Simulation and custom data acquisition pipelines, which together provided the backbone for responsive control logic.

Artificial intelligence enhances decision-making at the local agent level. Clustering algorithms, such as k-means, were used to classify workstation behavior and detect performance deviations, while rule-based agents made real-time logistics decisions based on OEE trends, buffer levels, and task priorities. Predictive analytics anticipated material shortages and bottlenecks, and feedback control logic employed threshold values and historical data to guide adaptive responses. This integration enabled autonomous agents to adjust their behavior to local conditions while contributing to the overall efficiency of the production system.

Decentralization is paramount to this model. Unlike traditional centralized systems such as MES or ERP, intelligence is distributed across the production network. Each component—workstation, buffer, or AMR—operates independently, but coordination is achieved through lightweight data exchange protocols. This architecture ensures scalability across factory sizes, fault tolerance in the event of local failures, and faster response times to disruptions without relying on central schedulers.

Ultimately, the model embodies a human-in-the-loop philosophy that aligns with Industry 5.0 values. AI does not replace operators but supports them by surfacing actionable insights and providing decision transparency. Real-time dashboards and simulation interfaces allow supervisors to track system behavior, validate agent decisions, and intervene when strategic judgment is required. In this way, digital twin and AI integration not only improve efficiency and resilience but also reinforce collaboration between autonomous systems and human expertise.

4.3 Lessons Learned from Industrial Case Studies

The decentralized optimization model was validated across five distinct industrial domains: chemical, food, metal, wood, and apparel manufacturing. Each case study offered unique insights into the adaptability, scalability, and performance of the system, while collectively confirming that AI-driven decentralized control and digital twin technology can be applied in both highly automated and human-centric environments. In the chemical industry case (Publication I), the focus was on developing a virtual factory that integrated heterogeneous sensor data for real-time monitoring. By coupling the digital twin with legacy systems through custom middleware, it became possible to translate between modern monitoring tools and existing PLC-based infrastructure. Even in this highly regulated sector, the introduction of decentralized agent logic reduced idle times at critical workstations and improved overall responsiveness, demonstrating that decentralized control can complement rigid infrastructures without requiring major overhauls.

The food industry studies (Publications II, IV, VI) focused on simulation-driven intralogistics optimization using AMRs and decentralized task allocation strategies. Idle times were primarily traced back to desynchronized transport cycles and limited coordination between material flow and workstation demand. These effects were mitigated when AMRs were deployed under decentralized control logic, enabling dynamic mission reassignment and improved flow synchronization. Digital twin–based simulation models provided a virtual environment for evaluating routing strategies, buffer sizing, and workstation coordination prior to physical implementation. The results demonstrate that decentralized, agent-based control can enhance throughput and flow stability in repetitive, high-frequency manufacturing environments.

In the metal industry case (Publication V), the emphasis was on industrial data analytics to improve shop floor transparency. Fine-grained OEE monitoring at the workstation level revealed inefficiencies that were hidden in aggregated, line-level indicators. Data analytics revealed micro-stoppages and hidden idle periods, providing managers with actionable insights to optimize resource allocation without requiring major workflow redesigns. Real-time visualization dashboards integrated with data collection enhanced both operator awareness and supervisory decision-making. This case validated the role of data transparency as a prerequisite for adaptive logistics and production coordination.

The wood industry case (Publication VII) focused on the application of virtual factory modeling in combination with AI-based clustering for OEE optimization. The virtual twin environment enabled experimentation with alternative layouts and process configurations, providing low-risk validation before making physical investments. Clustering techniques allowed proactive bottleneck identification and improved predictability in resource allocation, reducing reliance on trial-and-error planning. This case demonstrated the importance of simulation as a safe and effective environment for validating decentralized control strategies.

Finally, the apparel industry pilot (Publication VIII) evaluated the proposed model within a highly variable SME environment characterized by manual processes, small batch production, and operator-driven scheduling. The DIMUSA system integrated digital twin modeling, clustering-based performance analysis, and AI-supported logistics decision logic into a unified platform. Decentralized control concepts were adapted to accommodate human variability and unpredictable takt times, supported by the combined use of Lean principles and the DMAIC methodology. Although AMR-based logistics were not implemented in practice, the model conceptually included logistics agents to analyze and simulate material-flow coordination. Real-time system feedback provided human-centered decision support by uncovering hidden inefficiencies, aiding in intervention prioritization, and illustrating how decentralized AI-based control principles can be applied in resource-constrained SMEs environments.

Each industrial case study addressed a distinct set of operational challenges, and the decentralized model implemented provided case-specific solutions. In Case A (chemical), limited visibility of line events and buffer statuses was resolved through continuous data acquisition and digital twin-based monitoring. In Case B (food), transport delays and unbalanced buffers were mitigated by AMR task prioritization driven by real-time OEE and buffer conditions. In Case C (metal), fragmented machine data and micro-stoppages were clarified through integrated OEE tracking and workstation-level transparency. Case D (wood) benefited from early detection of layout bottlenecks through simulation-driven routing analysis, while Case E (apparel) saw improved takt stability and reduced idle time due to real-time task queue visualization and operator feedback integration (see Table 8). These cases collectively demonstrate how the proposed model addresses the practical inefficiencies identified in Section 3.2.

Across these cases, several overarching themes emerged (Table 11). A summarized view of the quantitative performance improvements in the industrial case studies is shown in Tables 7–10, which highlight the key KPIs, validation scenarios, adopted technologies, and links to relevant publications. These numerical results provide an integrated KPI summary for all industrial validations and support the qualitative lessons learned discussed in this section. Additional dataset examples used in the analyses—including AMR simulation outputs, real AMR movement logs, and workstation-level DIMUSA measurements—are included in Appendices 9–11, offering further transparency into the evidence base. The model proved scalable, with modular deployment strategies that began with OEE tracking and gradually expanded to full logistics integration.

It increased transparency, as real-time monitoring through digital twins improved operator trust and engagement. The system also enhanced resilience, with decentralized decision-making reducing vulnerability to delays, disruptions, and human error. Finally, the integration of Lean and DMAIC frameworks ensured that improvements were systematic, measurable, and sustainable. Across all pilots, measurable performance gains were observed in throughput time, workstation utilization, and reductions in idle periods, confirming the generalizability of the proposed model while underscoring the need to tailor solutions to sector-specific contexts.

Table 11. Cross-case synthesis: focus, key findings, applicability.

Sector	Focus	Key findings	Applicability of the model
Case A – Chemical industry	Real-time data, sensors, virtual factory	Middleware bridged PLC legacy, improving visibility; local agents reduced idle time at bottlenecks.	Fits regulated, process-centric contexts with strict data flows.
Case B – Food industry	AMR coordination, simulation, clustering	Decentralized AMR dispatch reduced idle; twins enabled routing/buffer tests pre-deployment	Strong where intralogistics dictates throughput
Case C – Metal industry	Data analytics, OEE transparency	Granular OEE revealed micro-stops; dashboards improved decisions	Effective even with fragmented data landscapes
Case D – Wood industry	Virtual factory + AI clustering	Early detection of layout bottlenecks; more predictable allocation	Scalable, supports proactive design changes
Case E – Apparel industry	DIMUSA twin, decentralized control	Handled human variability; synchronized flows; human-in-the-loop dashboards	Suits high-mix, manual, resource-constrained SMEs

4.4 Methodological Framework Based on Lean and DMAIC Principles

The development and implementation of the decentralized digital optimization and control model followed a structured DMAIC-inspired approach combined with Lean principles, ensuring that improvements were measurable, iterative, and grounded in real industrial data—the use of quantifiable indicators allowed for systematic validation of efficiency gains across the industrial cases.

From a Lean perspective, the main goal was to eliminate waste—especially waiting times, unnecessary transportation, and workstation idleness. The relationship between Lean principles and the digital optimization model is summarized earlier in Table 4. The KPI results, summarized in Table 9, demonstrate these improvements. For example, automation and decentralized logistics control reduced transportation defects by about 10%, improved on-time delivery by 5%, increased inventory turnover by 5%, and reduced transportation labor costs by 15%. These gains directly indicate reductions in waste and better flow efficiency.

The digital twin architecture further supported Lean implementation by offering real-time visibility into material flows, buffer states, and workstation utilization. This transparency enabled continuous detection of bottlenecks and idle periods, contributing to observable reductions in non-productive time across the food, apparel, and metal industries. OEE-based measurements also provided a consistent metric for identifying performance losses: in several cases, workstation idle time was reduced by 8–12%, while AMR-assisted operations ensured a more stable material supply and minimized logistics-induced downtime.

AMRs, functioning as intelligent agents, strengthened just-in-time delivery by reducing unnecessary transport movements and aligning material flow with actual production demands. As a result, takt flow became smoother, and disruptions caused by missing or delayed materials were significantly reduced—directly supporting Lean waste-reduction goals.

Overall, integrating Lean and DMAIC methodologies resulted in a more resilient, scalable, and human-centric optimization framework. The numerical results derived from KPI monitoring confirm that the proposed approach not only aligns with Industry 5.0 principles but also delivers measurable value by improving flow stability, reducing waste, and enhancing the adaptability of production logistics across diverse industrial contexts.

4.5 Proposed Model for Decentralized Optimization

The main result of this dissertation is a decentralized, AI-powered optimization and control model integrating production and logistics processes. The model integrates digital twin technology, autonomous decision-making agents, and real-time production data to enable dynamic coordination and maintain workstation efficiency. The proposed decentralized model consolidates the components introduced in Sections 3.3 and 3.4 and corresponds to the integrated architecture shown in Figure 10, which illustrates the system architecture and interaction between the digital twin and decentralized control agents. The model's architecture is modular, comprising four interactive layers. The **physical layer** includes production units, buffers, conveyors, AMRs, sensors, and human operators who interact within the production environment. Above this, the **digital twin layer** offers real-time virtual representations of all entities, continuously updated via IoT connections and PLC interfaces. This layer not only reflects the factory's current state but also simulates workflows, tests different control strategies, and stores historical data for ongoing learning. The third component is the **agent layer**, where each key node, such as a workstation, AMR, or buffer, is represented by a local agent. These agents monitor local status indicators, such as buffer levels, task completion, or OEE trends, and exchange data with neighboring agents through lightweight communication protocols. Based on predefined rules and AI algorithms, agents make local decisions that contribute to overall system efficiency. Ultimately, the **coordination and feedback layer** ensures that decentralized actions are aligned with global objectives. It incorporates system-level KPIs, such as throughput and WIP levels, applies clustering-based behavior analysis, and enables alerting and override mechanisms to keep human supervisors informed.

The model's operational flow begins with initialization, during which the digital twin receives production orders and resource states, while workstations register their readiness and buffer levels. During task assignment, workstations request material delivery from AMRs when buffers are low. AMR agents then negotiate tasks based on urgency, proximity, and historical performance. As tasks are executed, all system components log their states, and deviations from expected timing trigger local or global adjustments. Over time, performance data—such as OEE trends, idle periods, and bottlenecks—are analyzed to refine agent behavior and task-routing logic.

A practical example can be illustrated in the context of Case B – the food industry. When a production unit detects that its material buffer is nearly empty, its local agent issues a task request that indicates the urgency and buffer status. AMR agents evaluate requests from multiple workstations, consider their own location and battery levels, and choose the most efficient delivery path. If OEE for the workstation cluster drops below a critical threshold, the system issues an alert to a supervisor via the dashboard interface, allowing human intervention if needed. The proposed model offers several key advantages. It is modular and scalable, making it suitable for production environments of varying sizes and complexity, especially in small and medium-sized manufacturing settings. It is fault-tolerant because the modular structure enables automatic reallocation of tasks when a component fails. It involves human decision-makers in the process by making agent decisions transparent and overrideable. Finally, the model is adaptive by design: AI algorithms currently use data patterns to support decision-making, and the system architecture enables future extensions toward continuous self-learning and automated optimization.

4.6 Limitations and Risks

While the proposed decentralized optimization model has demonstrated clear benefits across multiple industrial contexts, several limitations and risks must be acknowledged to maintain realistic expectations for adoption and future development:

- From a technical perspective, one of the primary challenges is ensuring compatibility with legacy systems. Many existing manufacturing systems lack standardized interfaces or structured data formats, making it challenging to integrate the sensors and real-time pipelines required for digital twin operation.
- In addition, although the model is modular, large-scale deployments may face scalability constraints, as computational and communication loads increase with the number of agents. Without efficient synchronization, such systems risk delays or suboptimal decision-making due to data latency.
- A further challenge concerns data quality and availability: missing or noisy data from aging sensors or unstable connections can degrade the accuracy of AI predictions and weaken agent decisions.
- Finally, the well-known simulation–reality gap poses limitations: while digital twins are powerful for testing, they may oversimplify human behavior, equipment wear, or unpredictable events, reducing their predictive fidelity in real production.

The second category of risks is organizational and human-centric. Operator acceptance cannot be taken for granted, as workers may resist AI-driven task delegation or fear job displacement. A lack of transparency in agent decision-making may also generate mistrust and frequent process overrides. Additionally, concerns about data privacy—particularly regarding the monitoring of individual performance or workstation behavior—can further reduce acceptance unless clear safeguards and governance measures are in place. Moreover, decentralized systems require new competencies for setup, maintenance, and troubleshooting—both on the shop floor and in IT departments—which increase training demands. In specific regulated industries, process rigidity may also limit the scope of autonomy, since fully decentralized decision-making can conflict with strict quality assurance or safety requirements.

At the implementation level, several risks must be addressed. Initial setup is inherently complex, requiring the development of digital twins, configuring agents, and tuning decision thresholds. Of these, building the digital twin is generally the most time- and cost-intensive, as it demands detailed data integration and validation, whereas agent configuration and threshold tuning require less effort but still rely on expert input. Furthermore, cybersecurity is a growing concern: increased system connectivity and decentralized communication raise the risk of unauthorized access or data manipulation, particularly when cloud platforms are involved. Finally, the cost–benefit ratio of adopting decentralized optimization may vary. While the model offers clear advantages in high-volume or variable environments, its added value in low-volume or stable production settings may be less pronounced, where simpler coordination mechanisms may suffice.

To mitigate these risks, several strategies are recommended:

- A phased approach should be adopted, starting with hybrid models that combine human oversight with autonomous decision-making.
- Simulation and digital twin environments can be used not only for technical testing but also as training tools to familiarize operators with agent behavior. Deployment should start with non-critical workflows, gradually expanding as confidence in the system grows.
- Transparency should be supported through clear dashboards that explain and justify agent decisions, building trust among operators.
- Finally, cybersecurity protocols must be integrated from the planning phase, ensuring that resilience against external threats becomes an inherent property of the system.

Overall, recognizing these limitations and risks is essential for a balanced view of the model's potential. By proactively addressing them, the decentralized control framework can evolve into a more resilient, scalable, and human-centric solution that is better aligned with the strategic goals of Industry 5.0.

5 Conclusions and Future Work

This chapter concludes the doctoral thesis by summarizing the main contributions, discussing the broader implications for both research and industrial practice, and outlining avenues for future development. The work has centered on the design, implementation, and validation of a decentralized optimization and control model for production logistics. Through a synthesis of eight scientific publications, the research has advanced the integration of digital twins, AI-driven agents, and real-time performance data into a unified simulation-based control model. This model operates alongside the dissertation's methodological foundation, which builds on Lean principles and the DMAIC cycle, ensuring that the practical implementation and the theoretical approach remain clearly distinguished. Validation across both simulation and real industrial contexts confirmed the model's potential to increase throughput, reduce idle time, and support human-centric decision-making aligned with Industry 5.0 principles.

5.1 Summary of Contributions

This thesis contributes both theoretically and practically. The research strengthens the foundations of decentralized control theory and introduces methods for integrating artificial intelligence and digital twins into adaptive production systems. It employs a design science approach, structured around the DMAIC cycle to ensure measurable progress and iterative refinement during system development. Supported by digital twin modeling, simulation-based testing, and industrial validation across five sectors-Case A: Chemical industry, Case B: Food industry, Case C: Metal industry, Case D: Wood industry, and Case E: Apparel the research demonstrates how decentralized, AI-driven agents can enhance production efficiency, responsiveness, and transparency.

Theoretical contributions include:

- **Decentralized optimization model:** A system-level architecture in which workstations, buffers, and AMRs function as autonomous agents with local decision-making capability. Their actions are coordinated through shared performance indicators, enabling the system to optimize material flow and responsiveness without relying on a centralized dispatcher.
- **Integration of AI and digital twins**: Synchronization of real-time data streams with virtual factory models to enhance predictive capability and enable continuous feedback between physical and digital layers.
- **Agent-based decision logic**: Validation of rule-based and AI-assisted algorithms for dynamic task allocation and coordination, incorporating OEE indicators and flow constraints. The decision logic was implemented and tested across the different agent types introduced earlier in the architecture—**workstation agents**, **AMR agents**, and **buffer agents**—each operating with local information and lightweight communication to support decentralized control.
- **Clustering-based performance feedback**: Application of clustering to classify workstation behavior, supporting diagnostics, prioritization, and long-term system optimization.

Practical contributions include:

- **Industrial validation across diverse domains**: Demonstration of the model's benefits in Case A – Chemical industry, Case B – Food industry, Case C – Metal industry, Case D – Wood industry, and Case E – Apparel industry, showing measurable improvements in throughput, buffer utilization, and idle-time reduction.
- **Reusable simulation scenarios and models**: Creation of modular simulation environments adaptable for different layouts and transport setups, serving both research and industrial planning needs.
- **Implementation guidelines and risk insights**: Identification of practical barriers such as legacy integration, scalability, and operator acceptance, together with strategies for mitigation.
- **Open collaboration with industry**: Execution of research in cooperation with Estonian and international manufacturing firms, ensuring real-world relevance and facilitating knowledge transfer.

Answers to the research questions:

- **RQ1: How can a decentralized, AI-driven control model improve the coordination between production logistics and shop floor operations in dynamic manufacturing environments?**

  By distributing decision-making to local agents that respond directly to real-time OEE signals and buffer conditions, the model reduces waiting caused by material shortages or blocked outputs. This ensures that logistics missions are dynamically launched when needed, keeping workstations supplied and outputs cleared. Simulation and industrial cases confirmed that this synchronization reduced idle periods and maintained smoother production flow without relying on central scheduling (Publications II–IV, VI–VIII).

- **RQ2: What impact does such a model have on workstation efficiency, OEE, and overall throughput time?**

  The model improves workstation availability by ensuring timely material supply and removal, thereby directly enhancing OEE performance. Across simulation scenarios, throughput time was reduced by up to 15% in high-variance task sequences, and workstation idle times decreased significantly. Industrial pilots further confirmed measurable improvements in workstation utilization and overall flow efficiency (Publications II, III, VI, VIII).

- **RQ3: How can real-time data from digital twins be used to assign logistics tasks to a mobile robot dynamically?**

  Digital twins provide the live data backbone for task allocation, continuously synchronizing the state of workstations, buffers, and AMRs. Agents use this information to dynamically generate and negotiate logistics missions, combining urgency (OEE thresholds and buffer fill levels), proximity, and historical task durations. In practice, this enabled adaptive routing, congestion avoidance, and faster response to disruptions, thereby improving coordination between production and intralogistics (Publications I, VI, VII, VIII).

- **RQ4 (quantitative): To what extent can the proposed system reduce workstation idle time (%) and improve average throughput time (min) compared to baseline logistics coordination?**

  Quantitative validation shows measurable effects at various stages of the research. In the food industry case (Publication II), replacing manual transport with automated AMR-based logistics resulted in improvements across several KPIs, including fewer transport errors, better on-time delivery, higher inventory turnover, and reduced labor costs. The transport-event and AMR movement datasets supporting this analysis are documented in Appendix 9, which relates to Publications II and III.

  Further validation of decentralized control concepts was conducted in Publications IV and VI. The associated datasets for AMR coordination logic, task allocation, and system-level performance metrics under different load conditions are included in Appendix 10.

  In the apparel industry pilot (Publication VIII), validation was based on a combination of virtual factory simulations and real-time production data collected through the DIMUSA platform. Unlike the earlier simulation-focused studies, the key quantitative results for this case are reported directly in the main text (Table 8), where simulation-based OEE estimates are compared with real workstation measurements. This layered comparison revealed the limitations of purely simulation-driven assumptions and highlighted the importance of real-time data in capturing operator-induced variability and micro-batch effects.

Together, these findings confirm that the decentralized model delivers measurable reductions in idle time and throughput across different industries, from controlled simulations to SME pilots, while the integration of AI-generated logistics recommendations remains an open opportunity for future work.

5.2 Implications for Research and Practice

The results of this research extend beyond the specific industrial cases and carry significant implications for both academic inquiry and industrial digitalization strategies. Several notable contributions can be highlighted in academic research. The work advances decentralized control theory by providing an empirically validated architecture for distributed decision-making in complex production systems. Methodologically, it introduces a holistic research framework that integrates real-time data acquisition, clustering-based feedback mechanisms, and simulation-based validation, which can be applied in other domains of engineering and operations management. The research also reinforces the concept of human-centric manufacturing models, illustrating how adaptability, transparency, and AI support can be integrated into Industry 5.0 systems. Finally, the developed digital twin and agent-based models provide a reusable research platform for future studies, enabling the exploration of more advanced AI methods such as reinforcement learning, federated learning, or trust-aware agent systems.

For industrial practice, the findings provide clear directions for digital transformation. The proposed decentralized model contributes to operational efficiency, helping companies reduce throughput times and increase OEE, particularly in high-mix, low-volume environments where traditional centralized systems struggle. The modularity of the approach enables flexible logistics and layout planning, as factories can reconfigure workflows with minimal disruption. Notably, the model emphasizes workforce empowerment, augmenting operators rather than replacing them, with AI acting as a co-pilot that enhances transparency and acceptance. Ultimately, the work provides a strategic roadmap for digitalization, demonstrating how firms can gradually transition from ERP/MES-driven logistics to more autonomous and adaptive infrastructures.

5.3 Future Research Directions

While the research has demonstrated promising results, several avenues remain open for enhancing the adaptability, intelligence, and scalability of decentralized control systems.

- **AI learning and adaptation**: Future work should integrate reinforcement learning, online learning, or hybrid AI approaches, enabling agents to continuously refine task allocation based on historical performance, environmental variability, and operator feedback.
- **Inter-agent collaboration and communication**: Research is needed on negotiation protocols, decentralized consensus mechanisms, and conflict resolution strategies to strengthen coordination in highly dynamic production settings.
- **Scalability in large-scale production**: Expanding the architecture to hundreds of agents and thousands of tasks will require addressing latency, computational overhead, and emergent behaviors. This is particularly critical for complex factory layouts.
- **Cross-sector validation and transferability:** Further studies should expand testing across additional industrial sectors to confirm the model's adaptability, interoperability, and robustness under varying production constraints and automation levels.
- **Cybersecurity and trust in AI-driven control**: As systems become more autonomous and interconnected, ensuring secure agent communication, trust verification, and resilient failure recovery mechanisms will be essential for industrial adoption.
- **Human–AI collaboration interfaces**: Future studies should explore how explainable AI, intuitive dashboards, and shared-control paradigms can strengthen human trust and support decision-making in decentralized systems.
- **Integration with sustainability goals**: The model can be extended to incorporate environmental KPIs, optimizing for energy use, waste reduction, and material efficiency. AI-based control could thus strike a balance between productivity and ecological responsibility.
- **Cross-domain applications**: Beyond manufacturing, the principles developed here have potential in warehouse automation, healthcare logistics, and innovative infrastructure, where decentralized and adaptive coordination is equally relevant.

In conclusion, the research presented in this dissertation demonstrates that decentralized AI-based control can significantly enhance production logistics by increasing adaptability, resilience, and human-centered collaboration. At the same time, it opens new research opportunities at the intersection of digital twins, AI, and Industry 5.0. The future challenge and opportunity lie in scaling these solutions, securing their operation, and extending their benefits across both industrial and societal domains.

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References

1. Mahmood, K., Karjust, K. and Raamets, T. Production Intralogistics Automation Based on 3D Simulation Analysis. *Journal of Machine Engineering*, 2021, 21(2), 102–115. https://doi.org/10.36897/JME/137081
2. European Commission: Directorate-General for Research and Innovation, Petridis, A., De Nul, L. and Breque, M. Industry 5.0 : towards a sustainable, human-centric and resilient European industry. Publications Office of the European Union January 4, 2021. https://doi.org/10.2777/308407
3. Nahavandi, S. Industry 5.0—A Human-Centric Solution. *Sustainability 2019, Vol. 11, Page 4371*, 2019, 11(16), 4371. https://doi.org/10.3390/SU11164371
4. Demir, K. A., Döven, G. and Sezen, B. Industry 5.0 and Human-Robot Co-working. *Procedia Comput Sci*, 2019, 158, 688–695. https://doi.org/10.1016/j.procs.2019.09.104
5. Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., et al. Industry 5.0: Prospect and retrospect. *J Manuf Syst*, 2022, 65, 279–295. https://doi.org/10.1016/J.JMSY.2022.09.017
6. Maddikunta, P. K. R., Pham, Q. V., B, P., Deepa, N., Dev, K., Gadekallu, T. R., et al. Industry 5.0: A survey on enabling technologies and potential applications. *J Ind Inf Integr*, 2022, 26, 100257. https://doi.org/10.1016/J.JII.2021.100257
7. Seifermann, S., Böllhoff, J., Schaede, C., Kutzen, M. and Metternich, J. Novel method to systematically implement lean production in machining areas. *Procedia CIRP*, 2018, 78, 61–66. https://doi.org/10.1016/J.PROCIR.2018.09.059
8. Hoellthaler, G., Braunreuther, S. and Reinhart, G. Digital Lean Production-An Approach to Identify Potentials for the Migration to a Digitalized Production System in SMEs from a Lean Perspective. *Procedia CIRP*, 2018, 67, 522–527. https://doi.org/10.1016/j.procir.2017.12.255
9. Pongboonchai-Empl, T., Antony, J., Garza-Reyes, J. A., Tortorella, G. L., Komkowski, T. and Stemann, D. DMAIC 4.0 - innovating the Lean Six Sigma methodology with Industry 4.0 technologies. *Production Planning and Control*, 2025. https://doi.org/10.1080/09537287.2025.2477724
10. Singh, B. J. and Khanduja, D. Perspectives of control phase to manage Six Sigma implements: An empirical study. *International Journal of Business Excellence*, 2014, 7(1), 88–111. https://doi.org/10.1504/IJBEX.2014.057860
11. Soltanali, H., Rohani, A., Tabasizadeh, M., Hossein Abbaspour-Fard, M., Parida, A. and Student, P. D. Improving the performance measurement using overall equipment effectiveness in an automotive industry. *Int J Automot Eng*, 2018, 8(3), 2781–2791. https://doi.org/10.22068/ijae.8.3.2781
12. Uhlemann, T. H. J., Lehmann, C. and Steinhilper, R. The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0. *Procedia CIRP*, 2017, 61, 335–340. https://doi.org/10.1016/J.PROCIR.2016.11.152

13. Muchiri, P. and Pintelon, L. Performance measurement using overall equipment effectiveness (OEE): literature review and practical application discussion. *Int J Prod Res*, 2008, 46(13), 3517–3535. https://doi.org/10.1080/00207540601142645
14. Leitão, P., Barbosa, J. and Trentesaux, D. Bio-inspired multi-agent systems for reconfigurable manufacturing systems. *Eng Appl Artif Intell*, 2012, 25(5), 934–944. https://doi.org/10.1016/J.ENGAPPAI.2011.09.025
15. Dou, J., Chen, C. and Yang, P. Genetic Scheduling and Reinforcement Learning in Multirobot Systems for Intelligent Warehouses. *Math Probl Eng*, 2015, 2015(1), 597956. https://doi.org/10.1155/2015/597956
16. Block, C., Lins, D. and Kuhlenkötter, B. Approach for a simulation-based and event-driven production planning and control in decentralized manufacturing execution systems. *Procedia CIRP*, 2018, 72, 1351–1356. https://doi.org/10.1016/J.PROCIR.2018.03.204
17. Piccialli, F., Chiaro, D., Sarwar, S., Cerciello, D., Qi, P. and Mele, V. AgentAI: A comprehensive survey on autonomous agents in distributed AI for industry 4.0. *Expert Syst Appl*, 2025, 291. https://doi.org/10.1016/J.ESWA.2025.128404
18. Union, P. O. of the E., Dixson-Declève, S., Dunlop, K., Renda, A. and Charveriat, C. Industry 5.0 and the future of work : making Europe the centre of gravity for future good-quality jobs. Publications Office of the European Union July 12, 2023. https://doi.org/10.2777/685878
19. Longo, F., Padovano, A. and Umbrello, S. Value-oriented and ethical technology engineering in industry 5.0: A human-centric perspective for the design of the factory of the future. *Applied Sciences (Switzerland)*, 2020, 10(12), 1–25. https://doi.org/10.3390/APP10124182
20. Uhlmann, E., Polte, J. and Mühlich, C. Distributed real-time production control for resilient manufacturing systems. *Procedia CIRP*, 2023, 120, 1274–1279. https://doi.org/10.1016/J.PROCIR.2023.09.162
21. Kuczyńska-Chałada, M., Furman, J. and Poloczek, R. The Challenges for Logistics in the Aspect of Industry 4.0. *Multidisciplinary Aspects of Production Engineering*, 2018, 1(1), 553–559. https://doi.org/10.2478/MAPE-2018-0070
22. Daniyan, I., Adeodu, A., Mpofu, K., Maladzhi, R. and Kana-Kana Katumba, M. G. Application of lean Six Sigma methodology using DMAIC approach for the improvement of bogie assembly process in the railcar industry. *Heliyon*, 2022, 8(3), e09043. https://doi.org/10.1016/J.HELIYON.2022.E09043
23. De Mast, J. and Lokkerbol, J. An analysis of the Six Sigma DMAIC method from the perspective of problem solving. *Int J Prod Econ*, 2012, 139(2), 604–614. https://doi.org/10.1016/j.ijpe.2012.05.035
24. Gyulai, D., Pfeiffer, A., Nick, G., Gallina, V., Sihn, W. and Monostori, L. Lead time prediction in a flow-shop environment with analytical and machine learning approaches. 2018, 51(11), 1029–1034. https://doi.org/10.1016/J.IFACOL.2018.08.472

25. Lu, Y., Liu, C., Wang, K. I. K., Huang, H. and Xu, X. Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robot Comput Integr Manuf*, 2020, 61, 101837. https://doi.org/10.1016/J.RCIM.2019.101837
26. Eiskop, T., Snatkin, A., Karjust, K. and Tungel, E. Production monitoring system design and implementation. *Proceedings of the Estonian Academy of Sciences*, 2017, 66, 66. https://doi.org/10.3176/proc.2017.4.02
27. Adel, A. Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing 2022 11:1*, 2022, 11(1), 1–15. https://doi.org/10.1186/S13677-022-00314-5
28. Fogaça, D. R., Grijalvo, M. and Sacomano Neto, M. What Are Industry 4.0 and Industry 5.0 All About? An Integrative Institutional Model for the New Industrial Paradigms. *Administrative Sciences 2025, Vol. 15, Page 118*, 2025, 15(4), 118. https://doi.org/10.3390/ADMSCI15040118
29. Sufian, A. T., Abdullah, B. M. and Miller, O. J. Smart Manufacturing Application in Precision Manufacturing. *Applied Sciences 2025, Vol. 15, Page 915*, 2025, 15(2), 915. https://doi.org/10.3390/APP15020915
30. European Commission: Directorate-General for Research and Innovation. ERA industrial technologies roadmap on human-centric research and innovation for the manufacturing sector. Publications Office of the European Union July 30, 2024. https://doi.org/10.2777/0266
31. Xu, X., Lu, Y., Vogel-Heuser, B. and Wang, L. Industry 4.0 and Industry 5.0—Inception, conception and perception. *J Manuf Syst*, 2021, 61, 530–535. https://doi.org/10.1016/J.JMSY.2021.10.006
32. Sahoo, S. and Lo, C. Y. Smart manufacturing powered by recent technological advancements: A review. *J Manuf Syst*, 2022, 64, 236–250. https://doi.org/10.1016/J.JMSY.2022.06.008
33. Sundar, R., Balaji, A. N. and Satheesh Kumar, R. M. A Review on Lean Manufacturing Implementation Techniques. *Procedia Eng*, 2014, 97, 1875–1885. https://doi.org/10.1016/J.PROENG.2014.12.341
34. Reke, E., Powell, D. and Mogos, M. F. Applying the fundamentals of TPS to realize a resilient and responsive manufacturing system. *Procedia CIRP*, 2022, 107, 1221–1225. https://doi.org/10.1016/J.PROCIR.2022.05.135
35. Bokhorst, J. A. C., Knol, W., Slomp, J. and Bortolotti, T. Assessing to what extent smart manufacturing builds on lean principles. *Int J Prod Econ*, 2022, 253, 108599. https://doi.org/10.1016/J.IJPE.2022.108599
36. Dillinger, F., Kagerer, M. and Reinhart, G. Concept for the development of a Lean 4.0 reference implementation strategy for manufacturing companies. *Procedia CIRP*, 2021, 104, 330–335. https://doi.org/10.1016/J.PROCIR.2021.11.056
37. Brad, S. and Deeb, E. Integrating Lean Principles into Lean Robotics Systems for Enhanced Production Processes. *Systems 2025, Vol. 13, Page 106*, 2025, 13(2), 106. https://doi.org/10.3390/SYSTEMS13020106
38. Becker, J. and Nyhuis, P. The Production Logistic Theory as an Integral Part of a Theory of Production Technology. *Lecture Notes in Production Engineering*, 2015, Part F1151, 25–36. https://doi.org/10.1007/978-3-319-12304-2_3

39. Petri, M., Turi, A. and Mocan, M. Warehouse Redesign Challenges—Adapting Layout and Improving Process Flow. *Springer Proceedings in Business and Economics*, 2020, 635–646. https://doi.org/10.1007/978-3-030-44711-3_48
40. Kampf, R., Hlatká, M. and Bartuska, L. Optimization of Production Logistics. *Advances in Science and Technology. Research Journal*, 2018, 12(4), 151–156. https://doi.org/10.12913/22998624/100351
41. Stittgen, T. and Schleifenbaum, J. H. Towards Operating Curves of Additive Manufacturing Equipment: Production Logistics and its Contribution to Increased Productivity and Reduced Throughput Time. *Procedia CIRP*, 2020, 93, 14–19. https://doi.org/10.1016/J.PROCIR.2020.06.006
42. Johnson, D. J. A framework for reducing manufacturing throughput time. *J Manuf Syst*, 2003, 22(4), 283–298. https://doi.org/10.1016/S0278-6125(03)80009-2
43. Mohan R, R. A Throughput Time Study on Gemba through ABC Analysis for High Demand Product among Varieties of Products. *IOSR Journal of Mechanical and Civil Engineering*, 2013, 5(1), 57–59. https://doi.org/10.9790/1684-0515759
44. Nyhuis, P. and Wiendahl, H. P. Fundamentals of production logistics: Theory, tools and applications. *Fundamentals of Production Logistics: Theory, Tools and Applications*, 2009, 1–312. https://doi.org/10.1007/978-3-540-34211-3
45. Roser, C., Nakano, M. and Tanaka, M. Single simulation buffer optimization. *JSME International Journal, Series C: Mechanical Systems, Machine Elements and Manufacturing*, 2006, 48(4), 763–768. https://doi.org/10.1299/JSMEC.48.763
46. Iwan, R. Analysis of productivity improvement using line balancing method (study case assembling line in PT XYZ). *IOP Conf Ser Mater Sci Eng*, 2018, 453(1). https://doi.org/10.1088/1757-899X/453/1/012055
47. Tian, B., Kaul, H. and Janardhanan, M. Towards Self-organized Logistics Planning in Decentralised Production Systems via Agent-Based Modelling. *Lecture Notes in Mechanical Engineering*, 2023, 825–832. https://doi.org/10.1007/978-3-031-34821-1_90
48. Raamets, T., Karjust, K., Hermaste, A. and Kelpman, K. Virtual factory model development for AI-driven optimization in manufacturing. *Proceedings of the Estonian Academy of Sciences*, 2025, 74(2), 228. https://doi.org/10.3176/PROC.2025.2.26
49. Che Maideen, N., Budin, S., Sahudin, S. and Ab Samat, H. Synthesizing the Machine's Availability in Overall Equipment Effectiveness (OEE). *Journal of Mechanical Engineering*, 2017, 4(3), 89–99.
50. Van De Ginste, L., Aghezzaf, E. H. and Cottyn, J. The role of equipment flexibility in Overall Equipment Effectiveness (OEE)-driven process improvement. *Procedia CIRP*, 2022, 107, 289–294. https://doi.org/10.1016/J.PROCIR.2022.04.047
51. Nakajima, S. *Nakajima, S. (1988), Introduction to Total Productive Maintenance (TPM), Productivity Press, Portland, OR.* Productivity Press, 1988.

52. Soltanali, H., Rohani, A., Tabasizadeh, M., Hossein Abbaspour-Fard, M., Parida, A. and Student, P. D. Improving the performance measurement using overall equipment effectiveness in an automotive industry. *Int J Automot Eng*, 2018, 8(3), 2781–2791. https://doi.org/10.22068/ijae.8.3.2781
53. Raamets, T., Karjust, K., Hermaste, A. and Mahmood, K. Planning and Acquisition of Real-Time Production Data Through the Virtual Factory in Chemical Industry. *ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE)*, 2022, 2B-2021. https://doi.org/10.1115/IMECE2021-73080
54. Moor, M., Pakkanen, J., Raamets, T., Mahmood, K. and Riives, J. Industrial data analytics in manufacturing shop floor level. *AIP Conf Proc*, 2024, 2989(1). https://doi.org/10.1063/5.0189502
55. Jonsson, P. and Lesshammar, M. Evaluation and improvement of manufacturing performance measurement systems - the role of OEE. *International Journal of Operations & Production Management*, 1999, 19(1), 55–78. https://doi.org/10.1108/01443579910244223
56. Snatkin, A., Karjust, K. and Eiskop, T. Real time production monitoring system in SME. In *Proceedings of the 8th International Conference od DAAAM Baltic Industrial Engineering 19-21st*. Tallinna Tehnikaülikooli Kirjastus, Tallinn, 2012, 573–578.
57. Mncwango, B. and Mdunge, Z. L. Unraveling the Root Causes of Low Overall Equipment Effectiveness in the Kit Packing Department: A Define–Measure–Analyze–Improve–Control Approach. *Processes*, 2025, 13(3). https://doi.org/10.3390/pr13030757
58. Laurensia, J., Kosasih, W. and Salomon, L. Integration of Operational Performance and Eco-Indicators for Assessing Environmental Impacts of Manufacturing Processes in an Automotive Component Company. *J Sustain Sci Manag*, 2023, 18(9), 184–197. https://doi.org/10.46754/jssm.2023.09.0013
59. Park, K., Jo, S., Shin, Y. and Moon, I. Flexible material handling system for multi-load autonomous mobile robots in manufacturing environments: a hierarchical reinforcement learning approach. *Int J Prod Res*, 2025, 63(15), 5671–5691. https://doi.org/10.1080/00207543.2025.2461131
60. Lackner, T., Hermann, J., Kuhn, C. and Palm, D. Review of autonomous mobile robots in intralogistics: state-of-the-art, limitations and research gaps. *Procedia CIRP*, 2024, 130, 930–935. https://doi.org/10.1016/J.PROCIR.2024.10.187
61. Pizoń, J., Wójcik, Ł., Gola, A., Kański, Ł. and Nielsen, I. Autonomous Mobile Robots in Automotive Remanufacturing: A Case Study for Intra-Logistics Support. *Advances in Science and Technology. Research Journal*, 2024, 18(1), 213–230. https://doi.org/10.12913/22998624/177398
62. Pizoń, J., Wójcik, Ł., Gola, A., Kański, Ł. and Nielsen, I. Autonomous Mobile Robots in Automotive Remanufacturing: A Case Study for Intra-Logistics Support. *Advances in Science and Technology. Research Journal*, 2024, 18(1), 213–230. https://doi.org/10.12913/22998624/177398

63. Golova, J., Mahmood, K. and Raamets, T. Simulation based Performance Analysis of Production Intralogistics. *IOP Conf Ser Mater Sci Eng*, 2021, 1140(1), 012026. https://doi.org/10.1088/1757-899X/1140/1/012026
64. Raamets, T., Majak, J., Karjust, K., Mahmood, K. and Hermaste, A. Development of process optimization model for autonomous mobile robot used in production logistics. *AIP Conf Proc*, 2024, 2989(1). https://doi.org/10.1063/5.0189299
65. Jiang, Y., Li, M., Li, M., Liu, X., Zhong, R. Y., Pan, W., et al. Digital twin-enabled real-time synchronization for planning, scheduling, and execution in precast on-site assembly. *Autom Constr*, 2022, 141, 104397. https://doi.org/10.1016/J.AUTCON.2022.104397
66. Keith, R. and La, H. M. Review of Autonomous Mobile Robots for the Warehouse Environment. 2024.
67. Zhang, J., Yang, X., Wang, W., Guan, J., Ding, L. and Lee, V. C. S. Automated guided vehicles and autonomous mobile robots for recognition and tracking in civil engineering. *Autom Constr*, 2023, 146, 104699. https://doi.org/10.1016/J.AUTCON.2022.104699
68. Sharma, A., Kosasih, E., Zhang, J., Brintrup, A. and Calinescu, A. Digital Twins: State of the art theory and practice, challenges, and open research questions. *J Ind Inf Integr*, 2022, 30, 100383. https://doi.org/10.1016/J.JII.2022.100383
69. Ebni, M., Bamakan, S. M. H. and Qu, Q. Digital Twin based Smart Manufacturing; From Design to Simulation and Optimization Schema. *Procedia Comput Sci*, 2023, 221, 1216–1225. https://doi.org/10.1016/J.PROCS.2023.08.109
70. Ricondo, I., Porto, A. and Ugarte, M. A digital twin framework for the simulation and optimization of production systems. *Procedia CIRP*, 2021, 104, 762–767. https://doi.org/10.1016/J.PROCIR.2021.11.128
71. Cao, H., Söderlund, H., Fang, Q., Chen, S., Erdal, L., Gubartalla, A., et al. Towards AI-based Sustainable and XR-based human-centric manufacturing: Implementation of ISO 23247 for digital twins of production systems. 2025. https://doi.org/https://arxiv.org/abs/2508.14580
72. West, T. D. and Pyster, A. Untangling the Digital Thread: The Challenge and Promise of Model-Based Engineering in Defense Acquisition. *INSIGHT*, 2015, 18(2), 45–55. https://doi.org/10.1002/INST.12022
73. Mudgal, P. A Data-Centric Framework for Implementing Artificial Intelligence in Smart Manufacturing. *Electronics 2025, Vol. 14, Page 3304*, 2025, 14(16), 3304. https://doi.org/10.3390/ELECTRONICS14163304
74. Dobra, P. and Jósvai, J. Prediction of Overall Equipment Effectiveness in Assembly Processes Using Machine Learning. *Strojnicky Casopis*, 2024, 74(2), 57–64. https://doi.org/10.2478/SCJME-2024-0026
75. Javaid, M., Haleem, A., Singh, R. P. and Suman, R. Artificial Intelligence Applications for Industry 4.0: A Literature-Based Study. *Journal of Industrial Integration and Management*, 2021, 7(1), 83–111. https://doi.org/10.1142/S2424862221300040

76. Drakaki, M., Karnavas, Y. L., Tzionas, P. and Chasiotis, I. D. Recent Developments towards Industry 4.0 Oriented Predictive Maintenance in Induction Motors. *Procedia Comput Sci*, 2021, 180, 943–949. https://doi.org/10.1016/j.procs.2021.01.345
77. Shah, N., Shah, S., Bhanushali, J., Bhatt, N., Bhatt, N. and Mewada, H. The Future of Manufacturing with AI and Data Analytics. In *Artificial Intelligence-Enabled Digital Twin for Smart Manufacturing*. wiley, 2025, 541–564. https://doi.org/10.1002/9781394303601.ch23
78. Pashko, A., Oleshko, T. and Biesiedina, S. Stochastic Algorithms for Optimization of the Path of Robotic Systems. *Lecture Notes in Networks and Systems*, 2022, 463 LNNS, 227–236. https://doi.org/10.1007/978-3-031-03877-8_20
79. Nivetha, S. K., Asokan, R. and Senthilkumaran, N. Metaheuristics in mobile AdHoc network route optimization. *Proceedings of the 2019 TEQIP - III Sponsored International Conference on Microwave Integrated Circuits, Photonics and Wireless Networks, IMICPW 2019*, 2019, 414–418. https://doi.org/10.1109/IMICPW.2019.8933284
80. Huang, F., Zhu, Q., Zhou, J., Tao, J., Zhou, X., Jin, D., et al. Research on the parallelization of the DBSCAN clustering algorithm for spatial data mining based on the Spark platform. *Remote Sens (Basel)*, 2017, 9(12). https://doi.org/10.3390/rs9121301
81. Patel, V. R. and Mehta, R. G. Modified k-means clustering algorithm. *Communications in Computer and Information Science*, 2011, 250 CCIS, 307–312. https://doi.org/10.1007/978-3-642-25734-6_46
82. Puthanveettil Madathil, A., Luo, X., Liu, Q., Walker, C., Madarkar, R. and Qin, Y. A review of explainable artificial intelligence in smart manufacturing. *Int J Prod Res*, 2025. https://doi.org/10.1080/00207543.2025.2513574
83. Baroudi, U., Alshaboti, M., Koubaa, A. and Trigui, S. Dynamic Multi-Objective Auction-Based (DYMO-Auction) Task Allocation. *Applied Sciences 2020, Vol. 10, Page 3264*, 2020, 10(9), 3264. https://doi.org/10.3390/APP10093264
84. Javaid, M. A. Understanding Dijkstra Algorithm. *SSRN Electronic Journal*, 2013. https://doi.org/10.2139/SSRN.2340905
85. Lavalle, S. M. Planning Algorithms. In *http://planning.cs.uiuc.edu/*. Cambridge University Press, 2006, 842.
86. Raamets, T., Majak, J., Karjust, K., Mahmood, K. and Hermaste, A. Autonomous mobile robots for production logistics: a process optimization model modification. *Proceedings of the Estonian Academy of Sciences*, 2024, 73(2), 134–141. https://doi.org/10.3176/PROC.2024.2.06
87. Shrestha, S., Varma Appani, P., Reddy Kota, P. and Sheta, A. Optimizing Robot Path Planning in 2D Static Environments using GA, PSO and ACO Search Algorithms. *Int J Comput Appl*, 2024, 186(7), 975–8887. https://doi.org/10.5120/ijca2024923402
88. Morissette, L. and Chartier, S. The k-means clustering technique: General considerations and implementation in Mathematica. *Tutor Quant Methods Psychol*, 2013, 9(1), 15–24. https://doi.org/10.20982/tqmp.09.1.p015

89. Raamets, T., Karjust, K., Majak, J. and Hermaste, A. Implementing an AI-Based Digital Twin Analysis System for Real-Time Decision Support in a Custom-Made Sportswear SME. *Applied Sciences 2025, Vol. 15, Page 7952*, 2025, 15(14), 7952. https://doi.org/10.3390/APP15147952
90. Siderska, J. Application of Tecnomatix Plant Simulation for Modeling Production and Logistics Processes. *Business, Management and Education*, 2016, 14(1), 64–73. https://doi.org/10.3846/BME.2016.316
91. Shahri, E., Pedreiras, P. and Almeida, L. Enhancing MQTT with Real-Time and Reliable Communication Services. *IEEE International Conference on Industrial Informatics (INDIN)*, 2021. https://doi.org/10.1109/INDIN45523.2021.9557514

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Abstract

Development and Implementation of a Decentralized AI-Driven Control Model for Production Processes

This doctoral thesis focuses on developing and implementing a decentralized, AI-driven digital optimization and control model for manufacturing processes within the framework of Industry 5.0. The work addresses a common challenge in modern manufacturing: the misalignment between material flows and workstation needs, which often leads to idle times, bottlenecks, and delays in throughput. Unlike traditional centralized Manufacturing Execution Systems (MES), which impose rigid schedules, the proposed system empowers workstations, buffers, and autonomous mobile robots (AMRs) to operate as independent agents. Each agent makes local decisions independently but can share information with other agents when needed, ensuring coordinated material flows and better overall system efficiency.

The research builds on digital twin technology, Overall Equipment Effectiveness (OEE) monitoring, clustering analysis, and agent-based decision logic to develop a modular architecture that can adapt to changing shop floor conditions. The methodological foundation is the DMAIC cycle (Define, Measure, Analyze, Improve, Control), which guides systematic progress from problem identification to simulation and industrial validation. The dissertation is based on eight peer-reviewed publications, which cover conceptual design, simulation testing, and case studies across the chemical, food, metal, wood, and apparel industries.

Empirical validation shows measurable improvements in workstation availability, throughput time, and OEE. For example, replacing manual transport with AMR-based logistics reduced transport errors and labor costs, while AI-enhanced decision logic further improved responsiveness and workload balancing. Industrial pilots confirmed that even resource-constrained SMEs benefit from a lightweight digital twin, combined with clustering-based performance analysis, which increases transparency, reduces idle time, and provides insights for more informed production decisions.

The scientific innovation of this research lies in integrating decentralized AI logic with production logistics and embedding OEE as a real-time control signal. The practical innovation is demonstrated through industrial deployment, showing that independent agents, capable of exchanging information when necessary, can collectively improve flow stability, increase resilience, and support human-machine collaboration without replacing existing control systems.

In conclusion, the thesis offers both theoretical insights and practical tools for Industry 5.0. It shows that decentralized AI-supported control can reduce inefficiencies, enhance production flow, and promote a human-centric, adaptable, and sustainable manufacturing approach. Overall, the research contributes to the growing body of Industry 5.0 studies by demonstrating how decentralized AI-based control can bridge the gap between digital innovation and operational feasibility.

Lühikokkuvõte

Detsentraliseeritud tehisintellektipõhise juhtimismudeli väljatöötamine ja rakendamine tootmisprotsessides

See doktoritöö keskendub detsentraliseeritud, tehisintellektil põhineva digitaalse optimeerimis- ja juhtimismudeli väljatöötamisele ja rakendamisele tootmisprotsesside jaoks Tööstus 5.0 raamistikus. Töö käsitleb tänapäeva tootmises levinud probleemi: materjalivoogude ja tööjaamade vajaduste vaheline ebakõla, mis sageli põhjustab seisakuid, kitsaskohti ja viivitusi läbilaskevõimes. Erinevalt traditsioonilistest tsentraliseeritud tootmise juhtimissüsteemidest (MES), mis kehtestavad jäigad ajakavad, annab kavandatud süsteem tööjaamadele, puhvermäludele ja autonoomsetele mobiilrobotitele (AMR) võimaluse tegutseda iseseisvate agentidena. Iga agent teeb kohalikke otsuseid iseseisvalt, kuid saab vajadusel jagada teavet teiste agentidega, tagades koordineeritud materjalivood ja parema üldise süsteemi efektiivsuse.

Doktoritöö tugineb digitaalse kaksiku tehnoloogiale, seadmete üldise efektiivsuse (OEE) jälgimisele, klastrianalüüsile ja agentide põhisele otsustusloogikale, et arendada modulaarset arhitektuuri, mis suudab kohaneda muutuvate tootmispõranda tingimustega. Metodoloogiliseks aluseks on DMAIC tsükkel (Define, Measure, Analyze, Improve, Control), mis juhib süstemaatilist edasiminekut probleemide tuvastamisest simulatsiooni ja tööstusliku valideerimiseni. Doktoritöö põhineb kaheksal eelretsenseeritud publikatsioonil, mis hõlmavad kontseptuaalset disaini, simulatsioonitestimist ja juhtumiuuringuid keemia-, toidu-, metalli-, puidu- ja rõivatööstuses.

Praktiliste katsete tulemused näitasid mõõdetavaid paranemisi tööjaamade töövalmiduses, läbilaskevõimes ja OEE-s. Näiteks käsitsi transpordi asendamine AMR-põhise logistikaga vähendas transpordivigu ja tööjõukulusid, samas kui tehisintellektiga täiustatud otsustusloogika parandas veelgi reageerimisvõimet ja töökoormuse tasakaalustamist. Tööstuslikud katseprojektid kinnitasid, et isegi ressursipiiranguga VKEd saavad kasu lihtsustatud digitaalsest kaksikust koos klastrite loomisel põhineva jõudlusanalüüsiga, mis suurendab läbipaistvust, vähendab jõudeaega ja annab teavet teadlikumate tootmisotsuste tegemiseks.

Selle uurimistöö teaduslik innovatsioon seisneb detsentraliseeritud tehisintellekti loogika integreerimises tootmislogistikaga ning OEE sidumises reaalajas juhtimissignaalina. Praktilist innovatsiooni demonstreeritakse tööstusliku juurutamise kaudu, näidates, et sõltumatud agendid, kes on võimelised vajadusel teavet vahetama, saavad ühiselt parandada voolu stabiilsust, suurendada vastupidavust ja toetada inimese ja masina koostööd ilma olemasolevaid juhtimissüsteeme asendamata.

Kokkuvõtteks pakub väitekiri nii teoreetilisi teadmisi kui ka praktilisi tööriistu Tööstus 5.0 jaoks. See näitab, et detsentraliseeritud tehisintellektil põhinev juhtimine saab vähendada ebatõhusust, parandada tootmisvoogu ning edendada inimkeskset, kohanemisvõimelist ja jätkusuutlikku tootmisviisi. Üldjoontes annab see uurimistöö oma panuse Tööstus 5.0 valdkonna kasvavasse teadustöösse, näidates, kuidas hajutatud tehisintellektil põhinev juhtimine suudab ületada lõhe digitaalse innovatsiooni ja praktilise rakendatavuse vahel.

Appendix 1

Publication I

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PLANNING AND ACQUISITION OF REAL-TIME PRODUCTION DATA THROUGH THE VIRTUAL FACTORY IN CHEMICAL INDUSTRY

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ABSTRACT

The various production problems that have arisen are closely linked to the need of the digitize products, production equipment, and their processes. With the increasing use of innovative software and hardware solutions, it is possible to monitor production processes accurately in the real-time and to manage various planning decisions according to these digital models. Such digital models allow us to react quickly to the physical production problems and to solve and also predict them. Furthermore, the virtual factory as an integrated simulation model of production units, provides an advanced decision support capability. On the other hand, Industry 4.0, the new industrial revolution has increasingly been used in the industrial sector and its development has grown exponentially in recent years. Various production equipment and activities are connected via network sensors to the Internet, where a huge amount of data is generated, stored, and analyzed. Industrial Artificial Intelligence (AI) algorithms are being used to evaluate the collected data and to provide valuable information for planning operations. This new industrial age presents new trends and challenges in the data context, such as scalability, cyber-security, and big data.

Therefore, when it comes to collecting data from devices and workplaces in real time, it is also wise to analyze the necessity and efficiency of this data, using different artificial intelligence algorithms. Clean data generally enables to make efficient and effective management decisions in the future based, to ensure the highest possible efficiency in the production unit. This article outlines the principles of Industry 4.0, emphasizing the features, requirements, and challenges of Industry 4.0. Besides, a development of the virtual model of the production line, there is also developed virtual model of the Autonomous Mobile Robots (AMR). This gives a good opportunity to monitor and analyze the entire production cycle, including the throughput, lead time, and utilization of resources in a 3D simulation production environment. Moreover, the article focuses on collecting real-time data from the virtual production unit to analyze the methods and locations of data collection, which would provide the most valuable information about production data. Finally, based on the results of the collected data, the authors present and discuss the challenges and trends that lie ahead when the same data collection methods are being used for physical production units. A case study approach is used to demonstrate the relevance and feasibility of the proposed methods for real-time data acquisition in production, which uses the concept of internet of things technologies and 3D visualization.

Keywords: real-time monitoring, virtual factory, process digitalization, Autonomous Mobile Robots, 3D visualization

1. INTRODUCTION

Today's manufacturing companies are exposed to increasing competition in a globalizing economy, which places higher demands on the product price, quality, and delivery time. Consumer expectations for new goods are also growing, where the important focus is on manufacturing customer-based products [1]. Traditional approaches are difficult and economically detrimental to deal with such situations, which in turn leads manufacturing companies to adopt entirely new technologies to meet the growing demands of end-users and to remain competitive in a very short time front [2, 3]. This market pressure is mainly on small and medium-sized enterprises operating in a specific sector or with small production volumes.

With the rapid development of various recent software and hardware solutions, it is possible to plan production processes and products on virtual models. It is not necessary to use the company's physical resources such as energy, materials, physical space, etc. for preplanning. Production processes can be simulated using existing data and varied to achieve the best output [4].

The Internet of Things (IoT), which connects the physical environment to cyberspace, has increasingly been used to collect data in real-time from the physical world. It enables us to perform detection, identification, and operation through various electronic components, distributed in the environment and connected to the network, resulting in a cyber-physical infrastructure [5].

This combination enables us to integrate the company's Enterprise Resource Planning (ERP) systems, warehouse systems, and production equipment into one united management system and allows them to automatically exchange data between each other [6].

However, due to the diverse and large amount of data in the IoT systems described, it is necessary to test the virtual models in advance and then place these components in a real production environment. After that, there can get proper locations of the equipment and workplaces, which gives the most accurate and understandable picture of production processes [3].

The analyzed virtual model of the factory is based on theoretical assumptions and the concept of virtual production is adapted to a specific type of production. For example, we took a unit of a chemical plant and use the company's actual production data to build a virtual model. The company is a Small and Medium-sized Enterprises (SMEs) with a large product nomenclature and a small production volume. Simulation models need to be validated before their results can be used [7]. In the simplified production model, the production process data has been used to make sensor location selections. Therefore, the data obtained are indicative and not subject to validation.

2. VIRTUAL FACTORY

The concept of Virtual Factory (VF) has been used to plan, analyze and optimize the production processes and activities that are conducted on a factory floor. In many kinds of literature, a virtual factory is defined as a reliable and detailed simulation of a manufactory factory, such as VF describes an integrated simulation model of a factory floor that represent the major processes and sub-systems in the factory, and enhanced the decision support capability [8]. VF with the help of digital tools simulates the production process planning and control, which facilitates to optimize of production systems and provides flexibility in the process design before its real implementation [9]. VF is tightly connected with the production processes analyze and technical Key Performance Indicators (KPI) definition [10]. From one side it is important to analyze the production processes (productivity, working times, set-up times, quality, OEE) and prioritize the important KPI's dependent on the actual processes. From the other side there can be used this information as an input for real factory simulation [11]. Moreover, the VF environment also simultaneously supports the performance evaluation of production systems found on a factory floor, allows configuration and re-configuration of systems for testing different scenarios, and enables the ramp-up phase of production systems to be less time-consuming [12].

2.1 Real Factory Simulation

Digitalization, virtual modelling, and simulation of physical production systems have changed the thinking in different manufacturing companies, and this was the force to implement the virtual factory concept in their factory operations. Ford Motor Company has been using 3D virtual technology for the process simulation to evaluate the ergonomics, performance of work-cells, and cycle time prior to implementing a physical system into the production floor [13]. The same way simulation and virtual environment facilitate the Volvo Group to improve and optimizing their production plants. They create virtual model of the production environment in order to test changes like configuration and re-configurations before implementing the changes into the real plant [14]. Furthermore, many commercial software providers have introduced the solution for 3D design, simulation, and visualization of production plants, which enables the implementation of the VF concept.

2.2 Virtual Factory Model

The model of virtual production in a computer environment can be either a digital twin of the whole factory or a single production unit, where it is possible to design production processes as in a real physical production environment [15]. In the case of a virtual model, it is important to present the behavior of a real production system in a realistic and equally dynamic way, using physical factory data and defined KPI's. Based on this computer simulation, it is possible to modify different input and output data in the creation, evaluation, optimization, and selection of alternatives to existing production plans. Today, different software solutions for creating virtual models are available that allow to create of 3D realistic models and simulate production processes.

The model of the 3D virtual factory to be analyzed FIGURE 1 is a subdivision of the chemical industry, where mainly disinfectants and personal hygiene products are produced [16]. The factory 2D floor plan is modelled using 3D visualization software (Visual Components 4.2) on a 1: 1 scale virtual model of the factory. The plant consists of two large warehouses and a production area with 4 automatic production lines and 5 manual production lines. The movement of materials (bottles, caps,

boxes, labels, etc.) between the warehouses and the production area is simulated with AMR systems [17].
The production cycle of one product group from the intermediate warehouse of raw materials (1) to the warehouse of finished products (4) is examined FIGURE 1 [18]. AMR serves workplaces 1,2,3 and 4. At the ends of the production line (M) are workplaces L1 and L2. The task of these workers is to move the raw material from workplace 2 to workplace L1 and L2 to workplace 3.

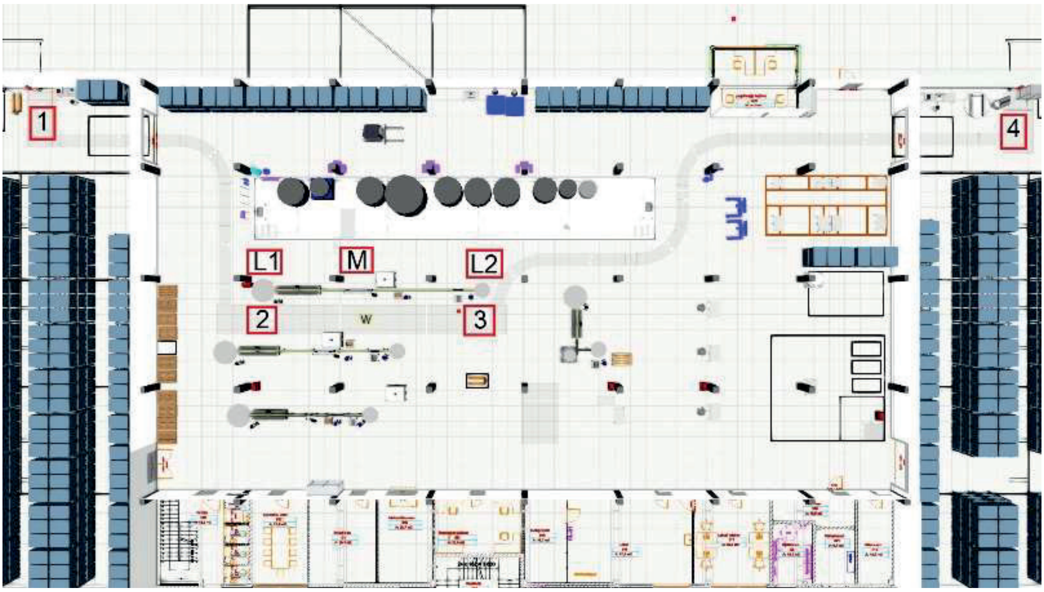

FIGURE 1: 3D MODEL OF A CHEMICAL INDUSTRY PRODUCTION UNIT

2.3 Simplified production unit model

Modelling an entire virtual factory with production processes is a relatively time-consuming job, so it makes sense to look at the monitoring of a specific product group and production line. This approach allows us to describe the entire production process and production logistics in more detail, which can later be transferred to other product groups and production lines. With the simplified model, it is possible to add all the important components that participate in the production cycle and give us a good overview of what is going on, and after that can easily change the process if the real data control from the factory floor gives the indication to make the changes. It is also easier and clearer to add different sensors here and present the obtained information graphically to analyze the generated data.
The developed simplified model FIGURE 2 consists of four AMR system workstations (1, 2, 3 and 4), two production line workplaces (L1 and L2) with operators and a production line (M).

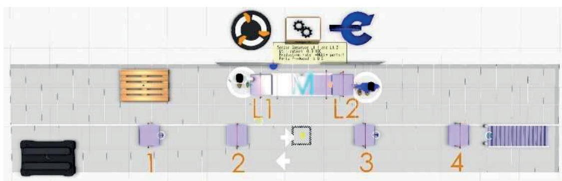

FIGURE 2: DEVELOPED PRODUCTION LINE MODEL

3. DESCRIPTION OF THE PRODUCTION PROCESS AND KPI SELECTION

In the chemical industry used in the simulation, the production activity usually takes place in one shift five days a week and the duration of the shift is 8 hours. The movement of all materials (bottles, caps, boxes, labels, etc.) between warehouses and production is carried out on euro pallets. Enterprise-wide production and inventory management are done through the company's ERP software, and the tasks and transport orders are assigned directly to the workshops. The company's automated production logistics and production flow chart from the raw material warehouse to the finished product warehouse is shown in the FIGURE 3 [19].

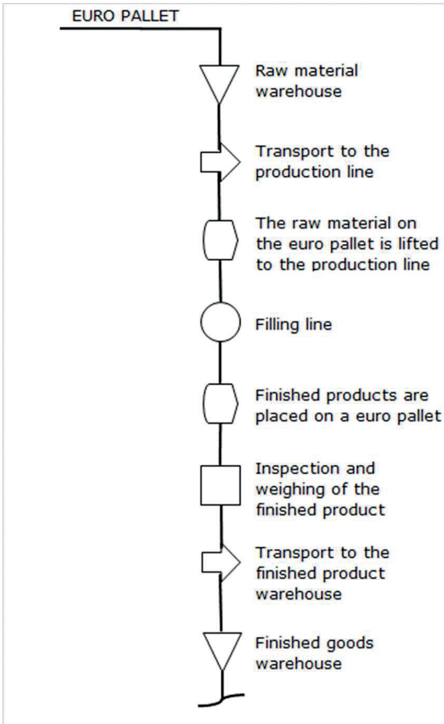

FIGURE 3: PRODUCTION PROCESS FLOW CHART

The most important parameter to describe the production flow FIGURE 3 efficiency is manufacturing cycle time, which is a set of transport operations, work processes, and breaks from the production of work objects to complete the production [19].
The formula for the manufacturing cycle time is given in the form (1):

$$\text{Manufacturing cycle time} = \text{Process time} + \text{Move time} + \text{Inspection time} + \text{Queue time} \quad (1)$$

where,

Process time refers to the time used to work on the product. Move time refers to the time required to transfer the product from one workstation to another. Inspection time is the time spent to check if the product is free from any defect. Queue time is the idle time the product spends waiting to be moved, processed, and shipped.

Based on the formula (1), to monitor and optimize manufacturing cycle time, the following time components in this production line need to be measured – transportation time from warehouse to filling line, filling time, inspection and weighting times, transportation time to the warehouse, and also all the waiting times that affecting the manufacturing time. To collect the so-called clean data from the production process, different sensors and data acquisition technologies must be installed on the production line.

4. SELECTION OF SENSOR INSTALLATION SCHEME

The rapid development of IoT technologies in manufacturing companies and real-time data collection have also found more use in company management processes. It is possible to point out some technologies, the use of which in production processes can give a great impetus to the development of the manufacturing industry precisely for gathering information from the production area and equipment [5].
The use of radio frequency identification (RFID) solutions is becoming increasingly attractive, especially for products where the shape, number, and other characteristics of the product vary and no direct visibility is required for identification [20, 21]. The price of this technology has also been on a downward trend over the years, and this provides an opportunity for wider use of this technology. RFID is an automatic identification technology in which objects are tagged and data is received wirelessly by signal transmission between a tag and antennas connected to a central server [21]. For example, an automatic material identification system using RFID technology allows us to track the location, quantity, origin, destination, and movement schedule of materials in real-time.
Wireless Sensor Networks (WSN) consist of spatially distributed autonomous nodes that can perceive the environment, perform calculations, and communicate with other nodes [21]. These sensor nodes operate in a self-organized and decentralized manner, ensuring the best and most stable data transmission to the central controller. Such a combination allows us to perceive the environment more precisely and to make more accurate production management decisions based on it. It can also be combined with RFID technology if objects cannot be identified using traditional sensor technologies [5].
Combining these two technologies, we find locations for the installation of sensors for the simplified production line model FIGURE 2. The selection and installation of the sensors are based on the manufacturing cycle time formula (1). and there was drawn up a sensor installation diagram FIGURE 4.

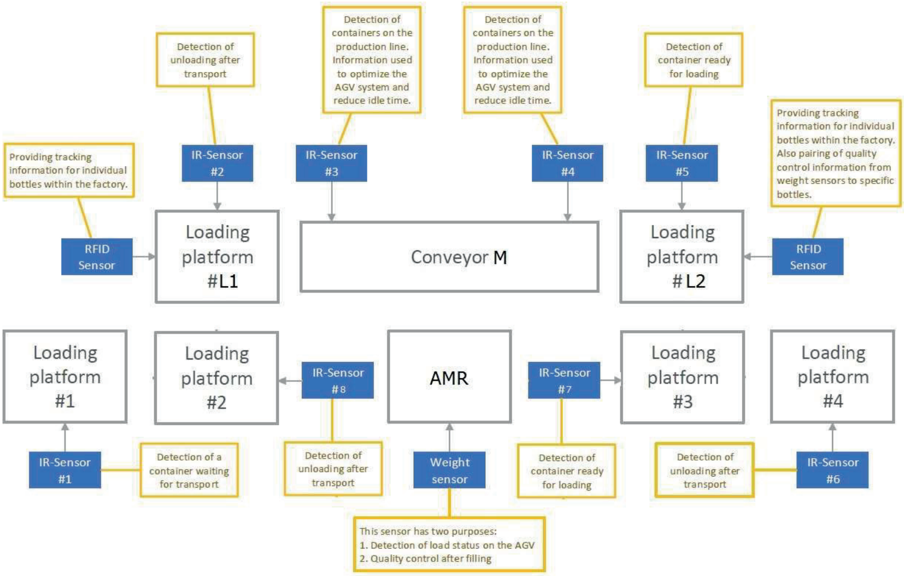

FIGURE 4: SENSOR SELECTION DIAGRAM IN WORKPLACE

The selection of sensors and the principles of their installation were described as shown in FIGURE 4. When selecting and installing these sensors, it is important to ensure that the raw data of the production cycle formula (1) and the cost of these systems are optimal. It is important for companies that the benefits of introducing such IoT systems outweigh the costs of this investment. RFID technology has been added for product tracking and quality assurance. On the one hand, this is important to ensure that the bottles are filled with the correct liquid, and on the other hand, it is a necessary input to ensure the quality of the product weight.
The simplified production model in FIGURE 2 shows the transport jobs (1,2,3 and 4), the production line buffer zone jobs (L1 and L2), and the production line (M). Transport orders are served by a AMR and one production worker at the workplace (2 and L1) and one worker at the workplace (L2 and 4). The production cycle starts at workplace 1 (raw material warehouse) and ends at workplace 4 (finished product warehouse). According to the production cycle formula (1), we find the inputs of the components. The processing time is the time spent on the product and takes place on the production line M. To find this time, there was installed two optical sensors on the production line at the beginning of one production line and the end of the other production line. On the production line, chains, caps, and liquids are added to the bottles and the product is finished. The optical sensor records the start and end times of the production process and its speed. For Move time, there was installed optical sensors 1,2, L1, L2,3 and 4 on the workstations, which show the arrival and departure of goods at these positions. It is also possible with these sensors to measure how long the goods are standing at these jobs and on this basis, to find the queue time. You can assign a specific name to a sensor and use it to determine its location in the model. The sensor works on the principle of a switch, when the goods arrive, switching takes place and when the goods leave the workplace, it is released and fixed in time. The RFID reader supports it in workstations L1 and L2. Each tare bottle that runs through the manufacturing process is equipped with an RFID passive sticker. An example of an RFID and optical sensor layout in a production unit is shown in the FIGURE 5. It is also an important component in ensuring an automatic quality control process. In addition, a weight sensor has been installed on the AMR which gives us information on whether the products have been placed on the robot, and in addition, quality control of the goods is performed at workplace

3. The system uses RFID data from workstation L2 as input and calculates the weight of the base with the goods. Weighing takes 30 seconds. If the weight corresponds to the predetermined weight, the process can continue, but if it does not meet, the weighing is repeated and if it does not, the pallet remains at position 3 and is counted in the inspection time. The whole process is supported by the company's ERP system and all the information collected from the sensors is stored and compared with the given data.
This ensures the traceability of the entire production cycle according to the production cycle formula (1). According to the sensor selection FIGURE 4, there was also added these sensors to the simplified production model shown in FIGURE 2.

FIGURE 5: RFID AND OPTICAL SENSOR PLACEMENT IN PRODUCTION

5. RESULTS AND DISCUSSION

All results presented in the paper are obtained using a simulation of a simplified production model FIGURE 2. To simplify the data obtained in the simulation, one item was used, which is one product (bottle). This approach allows us to display and analyze the results easily and clearly, both visually and numerically. It is important to understand whether this choice of sensor installation FIGURE 4 provides us with real-time traceability of the production cycle.
Based on the collected data from the sensors in the physical production line during the simulation, graphs of the cycle times of the sensors were plotted graphically FIGURE 6. Data were collected from 8 IR sensors and two RFID sensors. The weight sensor time was not measured because it is a software preset time (30 seconds) and it is displayed within the cycle time measured from the workplace 3 optical sensor. In a real production unit, this weighing time may change if, for example, a given weight does not match a given one. However, this already directly affects the time spent on quality control and it changes the inspection time in the production cycle.
The sensor cycle time graph FIGURE 6 shows the cycle times of the 8 IR sensors above and the cycle times of the 2 RFID sensors shown in the graph below. The sensor cycle time shows how long the sensor has been activated, i.e., how long the goods have been in the sensor's area of influence. The cycle times of the RFID sensors at the bottom of this graph also show the different product detection times of these sensors and are therefore good to use for product identification and to work with optical sensors to ensure data security. However, to get a more accurate time result directly from the sensors in contact with the product, and an optical sensor is suitable for this in our simulation.

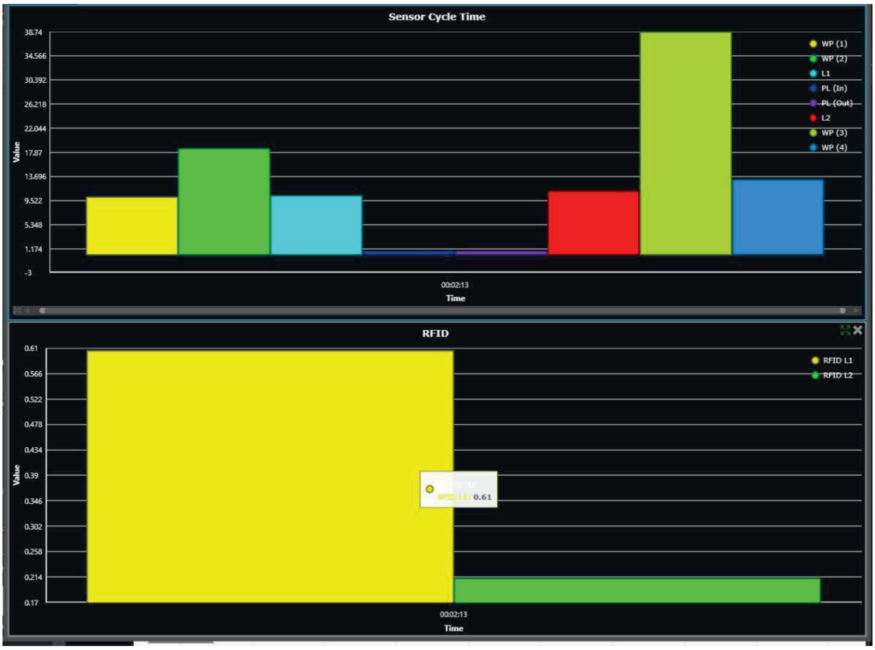

FIGURE 6: SENSOR CYCLE TIME RESULTS

TABLE 1 shows the cycle times of the optical sensors on the time axis, and here is also possible to get the start and end of the cycle time. Based on this data, it is possible to see what the entire product cycle time is and what it consists of.

TABLE 1:SENSOR CYCLE TIMES ON THE TIME AXIS

Simulation Time (s)	WP 1	WP 2	L1	M (In)	M (Out)	L2	WP 3	WP 4
1,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
11,3	10,3	0,0	0,0	0,0	0,0	0,0	0,0	0,0
13,5	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
32,1	0,0	18,6	0,0	0,0	0,0	0,0	0,0	0,0
36,2	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
46,6	0,0	0,0	10,4	0,0	0,0	0,0	0,0	0,0
48,8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
49,6	0,0	0,0	0,0	0,8	0,0	0,0	0,0	0,0
60,8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
61,6	0,0	0,0	0,0	0,0	0,8	0,0	0,0	0,0
63,8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
75,0	0,0	0,0	0,0	0,0	0,0	11,2	0,0	0,0
79,1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
117,8	0,0	0,0	0,0	0,0	0,0	0,0	38,7	0,0
122,1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
134,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	11,9

TABLE 2 shows the manufacturing cycle time and its components according to the manufacturing cycle time formula (1) and collected real time data.
The processing time is obtained as the difference between sensors M (In) and M (Out). Move time is obtained when goods are moved between workplaces (WP1, WP2, L1, L2, WP3, and WP4) also where the sensor signal indicates either the departure or arrival of the goods at the workplace.
The quality control time is fixed (30 seconds) and is deducted from the 3 waiting times of the workplace. Queue time is then the sum of downtimes read from the sensors, which is mainly the cycle time of the sensors.

TABLE 2:MANUFACTURING CYCLE TIME

Manufacturing Cycle time (s)	Process time (s)	Move time (s)	Inspection time (s)	Queue time (s)
134,0	12,8	14,7	30,0	76,5

The data obtained in Table 2 show that this selection of targeted sensors and locations gives us a good overview of the main components of the production cycle, and this data is easy to monitor and visualize. Also, with such a solution, the sensor data can be easily linked to the company's ERP systems to monitor a given production plan and compare it with the actual execution time. In addition, it is possible to analyze and visualize the impact of changes in production and logistics processes on the length of the production cycle.
This simulation of a simplified production unit or production line models provides a better overview of sensor placement and selection, and it is possible to get a faster overview of how these models work. If such a model has been tested and the necessary parameters are suitable for monitoring the production cycle time, then the next step is to transfer this selection of sensors to the

virtual model of the entire production unit and simulate it with real production data and goods quantities and test its solution. If for some reason, the data on the entire factory virtual model is incomplete or the location of the sensor does not match, these problems should be solved in advance on the simplified production unit model and then retested on the entire virtual factory model. Such a methodology provides an opportunity to better understand problems and find solutions to errors faster.
If a level has been reached on the virtual model of the factory that allows the data obtained from the sensors to be considered reliable and the time of the product production cycle can be monitored in each position, then a specific model of seniors' locations and their choices can be transferred to the actual production unit. Of course, there is also possible to calculate the cost of such a system in advance and make a list of the necessary components. In terms of hardware and software such solution provides an opportunity to understand in advance whether, is possible to use the existing hardware or software capabilities in the company. Today's production equipment is mostly equipped with various sensors and control units from which it is possible to read production data. In a specific chemical industry unit, this production line is already equipped with optical sensors at the input and output ends of the production line, which do not need to be additionally installed.

6. CONCLUSION

In the current study Virtual Factory model for chemical industry was developed. This VF model consists of the virtual model of production lines and Autonomous Mobile Robots between in the factory floor. During the work, methods for collecting real time data from the physical factory and integrating it into the virtual production unit to compare the simulation with the actual situation in the continuous loop were analyzed. During the process sensor selection diagram development with actual installation was done.
Data were collected from 8 IR sensors and two RFID sensors. The obtained data (manufacturing cycle time, process time, move time, inspection time, and queue time) show that this selection of targeted sensors and locations gives us a good overview of the main components of the production cycle, and this data is easy to monitor and visualize. With developed solution, the sensor data can easily linked to the company's ERP systems to monitor a given production plan and compare it with the actual execution time. It is possible to analyze and visualize the impact of changes in production and logistics processes on the length of the production cycle.
Measuring the production cycle and analyzing the data have a significant impact on the operations of the manufacturing company. Production capacity will increase, work in progress will decrease, efficiency will increase and production costs will decrease.

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REFERENCES

[1] J. Riives, K. Karjust, R. Küttner, R. Lemmik, K. Koov and J. Lavin, "Software development platform for integrated manufacturing engineering system," in *8th International Conference of DAAAM Baltic Industrial Engineering*, Tallinn, 2012.

[2] W. De Paula Ferreira, F. Armellini ja L. De Santa-Eulalia, „Simulation in industry 4.0: A state-of-the-art review," *Computers and Industrial Engineering,* kd. 149;106868, 2020.

[3] T. Eiskop, A. Snatkin, P. Tšukrejev, K. Karjust ja O. Märtens, „Design and Manufacturing of composite laminates with structural health monitoring capabilities," *Procedia CIRP ,* 2018.

[4] S. Jain, G. Shao ja S. S.J, „Manufacturing data analytics using a virtual factory representation," *International Journal of Production Research,* kd. 55:18, pp. 5450-5464, 2017.

[5] Y. Chen, S. Weiming ja W. Xianbin, „The Internet of Things in Manufacturing: Key Issues and Potential Applications," *IEEE Systems, Man, and Cybernetics Magazine,* kd. 4, nr 1, pp. 6-15, 2018.

[6] O. Labarre, "Enterprise Resource Planning (ERP)," [Online]. Available: https://www.investopedia.com/terms/e/erp.asp.

[7] T. Roeder, P. Frazier, R. Szechtman, E. Zhou, T. Huschka and S. Chick, "Standards based generation of a virtual factory model," in *Proceedings of the 2016 Winter Simulation Conference*, 2016.

[8] M. Mahmoodpour, K. Mahmood ja A. Lobov, „IoT-based senses for virtual enterprises," *IECON 44th Annual Conference of the IEEE Industrial Electronics Society,* pp. 4181-4186, 2018.

[9] M. Ghobankhloo, „Industry 4.0, Digitization, and Opportunities for Sustainability," 2019.

[10] M. Durkacova, J. Lavin and K. Karjust, "KPI Optimization for Product Development Process," in *23rd International DAAAM Symposium*, Austria, 2012.

[11] S. Kaganski, K. Karjust and J. Majak, "Prioritization of key performance indicators for small and medium enterprises," in *11th International Conference of DAAAM Baltic "Industrial engineering"*, Tallinn, 2016.

[12] W. Terkaj, T. Tolio ja M. Urgo, „A virtual factory approach for in situ simulation to support production and maintenance planning," *CIRP Annals – Manufacturing Technology,* kd. 64, pp. 451-454, 2015.

[13] J. Ford, "Ford creates virtual factory to simulate assembly-line proces," The Enigneer. [Online]. Available: https://www.theengineer.co.uk/ford-creates-virtual-factory-to-simulate-assembly-line-process/.

[14] E. Shellshear, R. Berlin ja J. Carlson, „Maximizing Smart Factory Systems by Incrementally Updating Point Clouds," *IEEE Computer Graphics and Applications,* kd. 35, pp. 62-69, 2015.

[15] M. Debevec, M. Simic, V. Jovanovic ja N. Herakovic, „Virtual factory as a useful tool for improving production processes," *Journal of Manufacturing Systems,* kd. 57, pp. 379-389, 2020.

[16] J. W. J. Y. T. J. Tomkins, Facilities Planning, United States of America: John Wiley & Sons, INC, 2010.

[17] L. Chengbao, T. Jie, Z. Hongsheng, L. Yaning and B. Xiwei, "Path planning and intelligent scheduling of multi-AGV systems in workshop," in *36th Chinese Control Conference (CCC)*, 2017.

[18] A. Carrie, Simulation of Manufacturing Systems, East: John Wiley & Sons Ltd., 1992.

[19] B. Joseph A ja S. Richard L, Time Based Manufacturing, New York: McGraw-Hill, Inc., 1993.

[20] I. Arkan ja H. Landeghem, „Evaluating the performance of a discrete manufacturing process using RFID: A case study," 2013.

[21] Y. Duroc ja S. Tedjini, „RFID: A key technology for Humanity," 2018.

Appendix 2

Publication II

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production logistics, mobile robots, intralogistics automation, 3D simulation, IoT sensors

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PRODUCTION INTRALOGISTICS AUTOMATION BASED ON 3D SIMULATION ANALYSIS

Recent trends in manufacturing such as Industry 4.0 and Smart Manufacturing have brought the researchers' attention to the smart intralogistics in production facilities. Automated guided vehicles (AGV), especially mobile robots play a vital role in this development. On the other hand, industrial internet technologies offered new possibilities for the information exchange between devices, data integration platforms and communication interfaces to advance and facilitate the intralogistics for effective material handling and transportation. In order to analyse the feasibility and effectiveness of the mobile robots in the production area, 3D visualization should be combined with simulation, which provides a comprehensive possibility to evaluate and review the potential solution performance and its consistency before implementing practically into the production floor area. This paper describes a conceptual model based on 3D visualization and simulation and experimental study which help to make the decision according to the input data from the factory environment of the movement of mobile robots in production logistics. Moreover, the Key Performance Indicators (KPIs) are defined to analyse the use-case's process improvement in terms of the time reduction, which leads to increase productivity and cut-down the workers' fatigue.

1. INTRODUCTION

Smart manufacturing demands the use of the technology and methods like: implementation of the Internet of Things (IoT) in factories and plants; integration of new technologies related to digital twin, augmented reality, and smart sensors for existing production environments. Those methods and technologies support the company management level for effective decision-making. The term that incorporates all those mentioned methods is known as “Industry 4.0”, a new word coined at the “Hannover Messe” held in 2011 [1]. The nine pillars of Industry 4.0 are: Big Data and Analytics, Autonomous Robots, Simulation, Horizontal and Vertical System Integration, IoT, Cloud Computing, Additive Manufacturing, Augmented/Virtual Reality (AR/VR), and Cyber Security [2].

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The technological roots for the Industry 4.0 are established by data networked production facilities, material handling as well as transporting equipment, which are harnessed with sensors and decentralized Information Technology (IT) intelligence. These intelligent systems for manufacturing intralogistics, which are connected via the Internet, are able to autonomously organize, control, and adapt the sequence of value-added processes and the correspondent logistical functions to exterior requirements. The recent "technology push" in the design and introduction of the autonomous production systems, advancement in digitalization, and automation leads to the expansion of new forms of services and work organization [3]. This new forms of services with collaborative machines, human, and transporting equipment such as Automated Guided Vehicles (AGVs) can be simulated to an extent, but they can be comprehensively understood with a level of trust for the adoption into the industry when the same scale experimental studies and demonstrators are established [4]. The combined effects of 3D simulation with the same level of real demonstrator help to make the efficient decisions and improvements of the target processes.

The high level of automation has been reached in production and intralogistics, but there is still use of human labour for the transportation of goods utilizing handcarts and forklifts, which leads to the higher labour cost and products quality risks. There are other approaches like the installation of conveyors to automate material handling and movement, but they are either fixed, overhead, or floor-based. Therefore, Autonomous Mobile Robots (AMR) are considered to be a potential solution for flexibility and to improve internal logistics efficiency. 3D visualization and simulation is an essential tool for the validation of the change in the real environment and facilitates to compare the different scansions virtually before the implementation [5, 6]. Besides that new industrial internet of things such as smart sensors, communication, and connectivity platforms add more value to the effective and efficient implementation of the change [7]. It helps to control and monitor the change i.e., deployment of AMRs in the real factory environment.

In this paper, authors contributed by developing a conceptual model to analyse the automation of intralogistics for manufacturing, which is based on autonomous mobile robots, 3D visualization and simulation, and IoT sensors for communication. A case study of a food production company was used to demonstrate the relevance and feasibility of the proposed concept.

The proposed concept allows SMEs to integrate the smart technologies of simulation, mobile robots, and IoT sensors to their current intralogistics system, which enables to improve the on-time delivery and reduce the labour costs and fatigues.

2. LITERATURE REVIEW

The literature review introduces the state of the art, which is related to the field of this study. It consists of the importance of 3D simulation and visualization, followed by the involvement of autonomous mobile robots for intralogistics, the brief explanation of IoT sensors, and vision technology. Moreover, similar studies and relevant approaches are also referred to in this section.

2.1. 3D SIMULATION AND VISUALIZATION

The purpose of the simulation is to grasp the insight behaviour of a system. Simulation is beneficial and appropriate to perform experiments and testing different solutions without any expense of physically change of a system, which allows to create an effective production line easier and quicker to accomplish. The ability to animate the system behaviour with time is one of simulation's great advantages. Animation is useful for demonstrations, validation, and debugging [8].

The extensive and often schematic 2D simulation & visualizations are not able to fulfil such objectives. One possibility is to use Industrial Virtual Reality (IVR) based 3D visualizations, which can be fitted to existing 3D assembly layouts, 3D product models, and process flows generated from simulation models [5]. During this work the purpose is to visualize the simulations at a particular area of the production floor in combination with a realistic representation of the area, besides, the step of assembly or filling of products including the components and tools are used, and the changes in the location of transportation equipment also addressed. This kind of visualization allows a good evaluation of the simulated sequences, which drives beyond established standard 2D simulation and visualizations [9]. 3D simulation and visualizations of intralogistics operations can be created by integrating the existing production process data and with the 2D layout of the production facilities.

2.2. AUTONOMOUS MOBILE ROBOT FOR INTRALOGISTICS

Material Handling Equipment (MHE) is a critical part of material flow for production factory logistics. For more flexibility in the production facilities, new transportation, and material handling methods need to be introduced [10]. MHE such as conveyors, used for automatic material transfer, and a large amount of parts can be moved, they offered temporary buffers, and material transportation between workstations, and they can be provided adequate solution together with forklift and pallet truck [11]. However, these equipment and systems allow a low degree of flexibility in routing compared to the AGVs and autonomous mobile robots. Moreover, autonomous mobile robots show a high level of versatility, as they can be used in various applications and can be reprogrammed depending on the input data changes. There are several developments and implementation of Industrial Robots (IR) into production facilities for the material handling and the different processes applications. Such as IR for the measurement process, the integration of IR in a manufacturing cell for pick and place, also in welding process [12, 13]. Conversely, there is still a need to do research and study regarding the usage and implementation of mobile robots for material handling in the production field, and how mobile robots can be combined with the industrial internet of things for effective decision-making and improvement of a transportation process.

As the new industrial internet of technologies, smart sensors, and development in artificial intelligence enabled positioning and autonomous navigation for mobile robots, which makes these vehicles to drive in a predefined area not as rigid to move in a defined guided path, that allows larger flexibility. Autonomous mobile robots operate on a decentralized decision basis, which leads to dynamic routing and scheduling. They are supposed to be small and more agile than traditional AGVs [14]. Furthermore, autonomous mobile robots can fit and access more areas and can be integrated to a higher degree in production workspace, leads to manufacturing flexibility and capable to fulfil the production demands. They are particularly suited for intralogistics operations like transportation and part feeding inside the production facility [10].

2.3. IoT SENSORS AND VISION TECHNOLOGY

Due to the recent development in modern manufacturing, most of the production and material handling systems are comprised of embedded technologies like smart sensors, organized through cloud-based solutions. It permits a large amount of data generation and collection that can be used to estimate different KPIs and enables proactive decision making. The ultimate aim of IoT applications in manufacturing is to comprehend smart factories, where machines and material handling resources communicate and are connected in a network. For that purpose, production lines, transportation resources, and existing IT tools of an enterprise should be connected to the internet directly or through external adapters [15].

Autonomous navigation can be achieved by integrating the applications of sensors, cameras, and computer vision into a vehicle. By using the camera and the object detection algorithm, certain 3D details on the motion path can be calculated and transmitted to the robot controller. This information notifies the robot controller about the desired location to be reached and facilitates navigation [16]. Likewise, autonomous navigation can be planned based, where a global map is used and relies on accurate global self-localization which is able to follow a path stated in global coordinates. In a planned based method, a path is defined at first on an available global map that is followed by the mobile robot. Different sensors and cameras can be used for localization in a map-based navigation approach.

2.4. LIMITATIONS IN EXISTING LITERATURE

This paper proposes a concept to analyse the automation of production logistics in a timely and coherent way, which is based on 3D simulation, autonomous mobile robots, smart sensors, and KPIs evaluation. There are studies and approaches covered the topic of automation of intralogistics and the use of mobile robots for transportation in production factories [10, 17, 18]. For production companies, such approaches and tactics are difficult to construct and adopt. Moreover, there are studies about the increased flexibility in intralogistics by suitable learning scenarios to grasp the energy-related dependencies of various transport technologies [19] and implementation of an autonomous industrial mobile robot in industrial applications that considered mobile robot technology, planning and scheduling, and communication [20]. However, they are lacking in the exploration of simulation and visualization tools, also recent studies are hardly providing a synchronized way to investigate the automation of intralogistics. This work provides a harmonized conceptual model to evaluate the automation of production logistics via simulation and mobile robots. For more flexibility in the production facilities, new transportation, and material handling methods need to be introduced [10]. Mostly used MHE such as conveyors used for automatic material transfer, forklift and pallet truck as mechanized material transportation equipment. However, these equipment allow a low degree of flexibility in routing compared to the AGVs and autonomous mobile robots. Moreover, mobile robots show a high level of versatility, for they can be used in various applications and can be reprogrammed as desired.

3. CONCEPTUAL MODEL AND CASE STUDY

The development of the conceptual model to analyse and implement the change i.e., automation of intralogistics for manufacturing was established. The case study practice was used as a research method. The general conceptual model is brought out in Fig. 1.

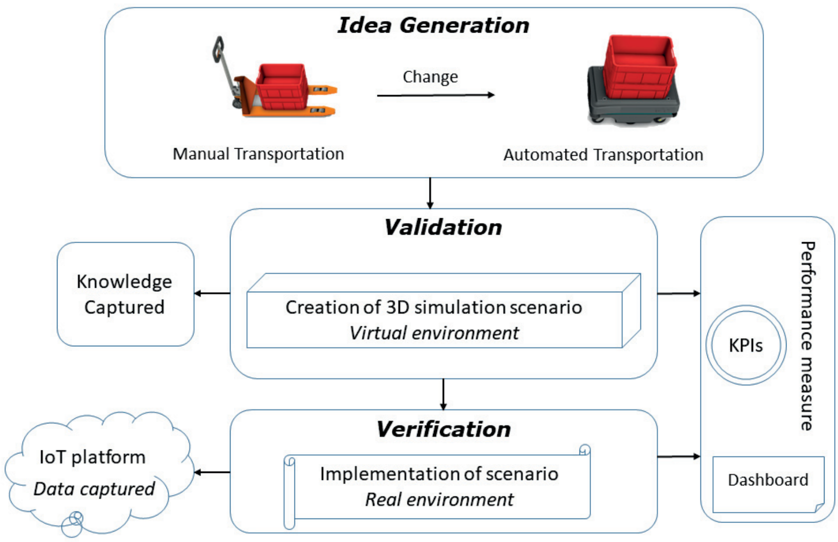

Fig. 1. General conceptual model to analyse the automation of production logistics

The model consist of three main steps, first is the idea generation, which is about the particular activity that should be automated and the purpose of the automation. The second step validates the change or implementation of mobile robots for transportation in a virtual environment, also facilities to compare the scenarios based on target KPIs and the knowledge should be used for the deployment of mobile robots in the real environment (third step). In the third step, data (movement of robots) should be captured from the real scene via a smart sensor and navigation plan, where the IoT platform used for the connectivity of different resources and storing data, which is later used for the estimation of KPIs. The third step not only verifies the virtual environment setup (layout and simulation), but also helps to prove the estimated KPIs from the simulation results.

3.1. DESCRIPTION OF A CASE STUDY

The proposed conceptual model was applied to a food manufacturing company intralogistics process, the company produces and sells prepared foods. Although, the company has the combined elements of flexibility and capacity in terms of production volume and product portfolios, which facilitates them to accomplish not only industrial but smaller-scale orders as well. However, most of the production activities are operated manually, especially the production floor logistics. The transportation and material handling of goods (raw material, WIP, and finished products) are one of the key activities on the production floor, and the improvement in this process by means of time reduction helps to increase productivity and cut-down the workers' fatigue. Therefore, the company intends to explore and adopt the automation possibilities in production logistics, and the idea was to implement autonomous mobile robots for the material transportation within the production floor and the company was keen to adopt this change i.e., the collaboration of mobile robots and workers.

The production facility handles the transportation of boxes (containers) by human-worker using hand lifters and special wheels. Approximately 4000–5000 red boxes are moving daily in production. In the case of logistics, the waybills (bill of materials) are used and the order is executed through oral commands. In this experiment, three basic logistics routes are considered and their respective workflows are:

- WF-1 – The transport-worker periodically reviews the production units and evaluates the number of boxes needed to move somewhere. Empty boxes are transported from the washing department to a special wheel-base;
- WF-2 – The production worker takes boxes for the production unit and brings them to the production line. When the products are ready, they put the goods in the boxes and transport them to the warehouse;
- WF-3 – The warehouse worker puts the raw material into the boxes and carrying them to the transport-base. The warehouse worker carries these wheel-bases to the intermediate storage of raw material.

3.2. KEY PERFORMANCE INDICATORS FOR ANALYSIS

Proper KPI selection, estimation and implementation are prerequisites to enhance the performance of the production processes [21, 22]. To keep in mind, the desired goals of automation and criticality of the logistic process, four major KPIs were defined to analyse the performance of the intralogistics process and compare the current situation (a manual process) with the automated production logistic via mobile robots. The KPIs used to measure the performance are:

P_1 – Defects during the transportation
P_2 – On-time delivery
P_3 – Inventory turnover
P_4 – Labour cost for transportation

Defects during the transportation were the irregularities in the number of boxes transported, transported at the wrong place, and incorrect goods transported. Those defects are caused due to the messy corridors, worker's fatigues, and lack of right information.

On-time delivery is the delivery of empty red boxes on-time at designated places in the production area. It helps to ensure the availability of empty boxes in a sufficient amount so that there is a reduction in waiting time for empty boxes and subsequently increment in on-time delivery.

Inventory turnover – one of the goals was to fill empty red boxes with finished goods (from production lines). It means to turn empty boxes into full boxes and can be defined as:

Average Inventory (I) = Throughput (R) x Average Flow Time (T)

Hence, *Inventory turnover = R / I*

Labour cost for transportation helps to realize the impact of mobile robots in monetary terms. The deployment of mobile robots leads to reduce the labour cost for transportation. Simple costing can be formulated as:

Cost = Investment + Operating cost (fixed and variable)

Although, there are initial investments to acquired mobile robots. However, after the payback period, there would be an increment in profit margin.

3.3. CREATION OF 3D SIMULATION SCENARIO

The simulation model of the case production facility can be seen in Fig. 2, Fig. 3 and Fig. 4 which were created on the Visual Components (VC) 4.2 [23]. The main focus is to set-up the production layout and simulates internal logistics. The target is to analyse the transportation of boxes (red colour boxes) that are used to carrying raw material from the warehouse to the production area, finished goods from the production area to the warehouse, and empty boxes from the washing area to production. The workplaces with different colours (red, yellow, and green) in Fig. 2 corresponds as follows:

- Red workplaces are the buffer for empty boxes
- Yellow workplaces are the buffer for Raw Material (RM)
- Green workplaces are the buffer for Finish Goods (FG)

The purpose of Fig. 2 is to define the designated working areas that were used in the factory floor for analysis and it helps to measure the distances between the working areas as well. Later those distances were capitalized to adjust the speed of mobile robots and use as an input parameter during the simulation. Figure 3 defines the routing map of mobile robots on a full scale and helps to plan the movement of mobile robots in the simulation environment.

The 2D factory floor map with the exact physical dimensions was imported into the virtual world and 3D environment of 1x1 scale was ramp-up on it, it represents the digital replica of the physical factory. The floor lines are clearly visible and the movement of AMRs can be observed i.e., the transportation of boxes by AMRs from the designated buffer areas to the production area on the factory floor and vice versa. It assists to find out the distance covered, time consumed and boxes transferred by AMRs during the simulation that aids to formulate the defined KPIs and later used for the comparison of manual transportation versus automated transportation by AMRs as criterions. Furthermore, Fig. 4 shows the 3D simulation of the factory floor for the holistic visualization and evaluation of the transportation of boxes via mobile robots.

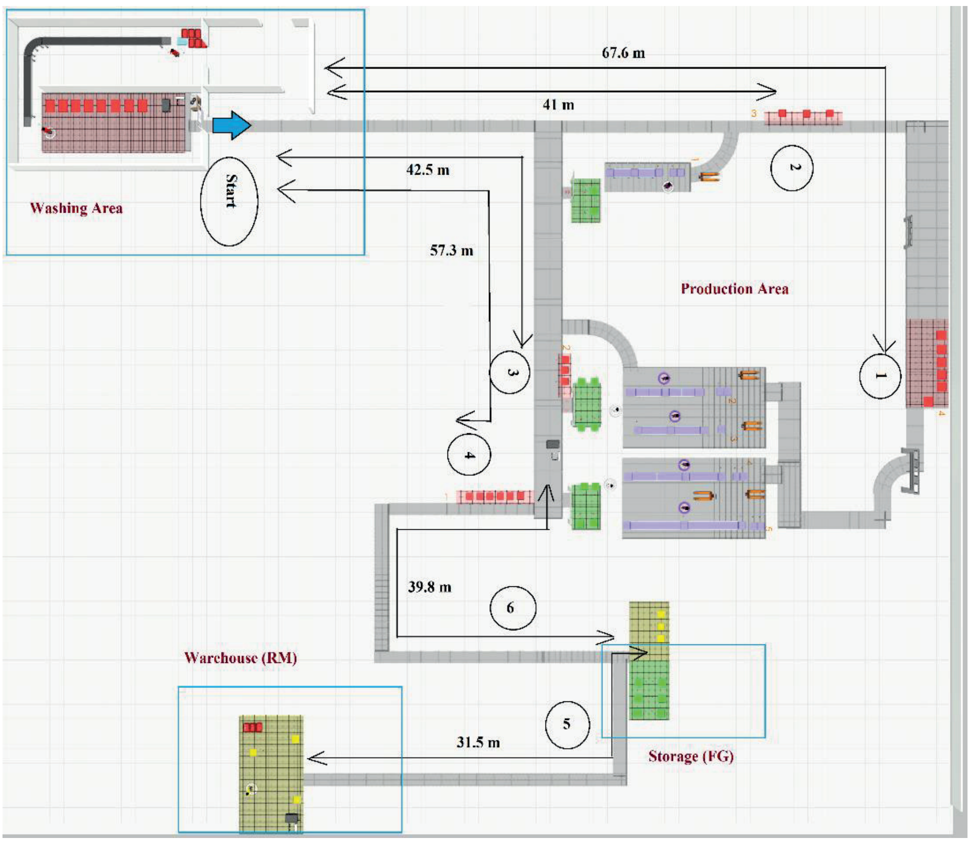

Fig. 2. Simulation scenario of production facility with the marking of working areas

AMRs were deployed to transport the boxes from one place to another in the virtual environment. There is the movement of 4000 boxes approximately in the production facility for the processing of different products in 12 hours. The major concern is the availability of empty boxes at red workplaces (buffer) at the right time, as those empty boxes are being used to store the ready products and then transport to the warehouse.

Fig. 3. Simulation scenario of production facility with the marking of mobile robots' routes

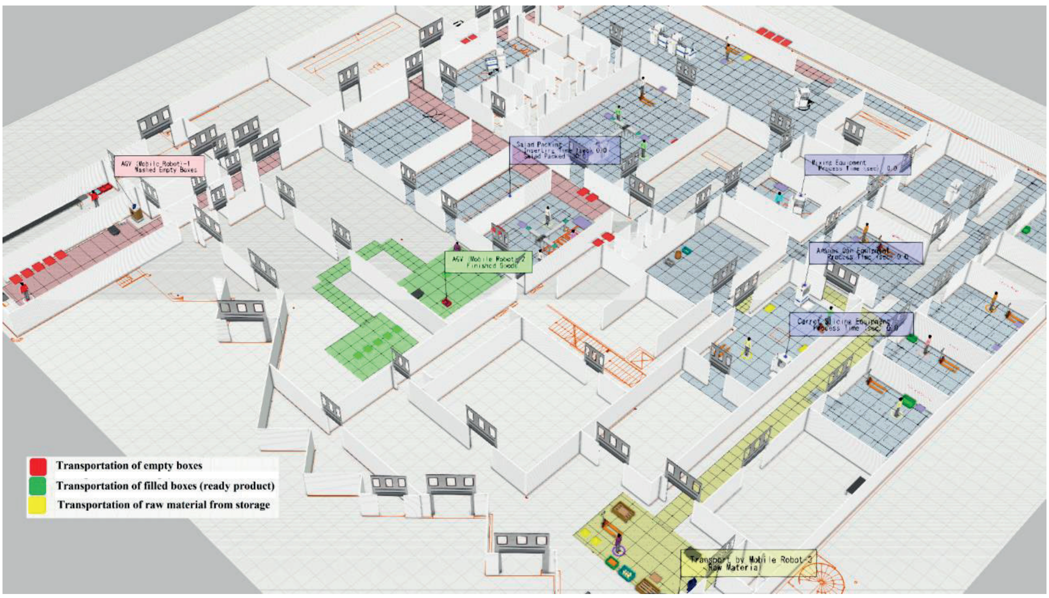

Fig. 4. 3D simulation model of production facility (virtual environment: a holistic view)

There are three AMRs, each is designated to different areas such as transport empty boxes from the washing area, raw material from the warehouse, and finish goods from production respectively. The process steps are as follows:

- AMR-1 – transports empty boxes from the washing area to different designated locations (red buffer) in production. AMR-1 carried 20 empty boxes in each run.
- AMR-2 – transports a box of raw material in each run to a particular location (yellow buffer) in the production area.
- Production workers pick the empty boxes from the designated locations, bring to the production lines, and filled boxes with products.
- AMR-3 – picks the filled boxes from the production area and transport them to the finish goods area (green buffer).

3.4. IMPLEMENTATION OF SCENARIO IN REAL ENVIRONMENT

The 3D simulation model (virtual environment) was implemented in the production facility (real environment) to verify the deployment of mobile robots for the production logistics process. The communication model of various devices such as mobile robots and sensors that were installed for the experimental study is shown in Fig. 5. The Hybrid Production System (HPS) was designed to enable interoperability and collaboration between different sub-systems. The HPS enables the integration with hardware devices and software of the end-users such as, for example, on the one hand the mobile robots and sensors in the warehouse, and on the other hand, the enterprise applications such as ERPs, MES and so on. The IoT Nodes layer (agent nodes) are the components of the communication model that interact with the physical world. For instance, they can interact by sensing, e.g., sensor agent node, by acting, e.g., robotic agent nodes. The modules of which these nodes are made of, can interact with the layer of Software System by exchanging messages with the layer of Cyber Physical Middleware and they either directly operate on these messages or translate them to an appropriate format for internal use through their communication sub-modules. Moreover, IoT nodes layer can talk to each other and with the other components of the communication model, as well as with Enterprise Applications, by means of the Cyber Physical Middleware layer. Similarly, the software applications layer interact with IoT nodes layer in addition to Enterprise Applications by means of message exchange via Cyber Physical Middleware.

The Human Machine Interface (HMI) module provides the task monitoring and control, which enables continuous monitoring and visualization of information connected to other modules such as the sensor module [24, 25]. HMI can collect data from enterprise applications. Furthermore, it can be used for the task specification to formulate a task based on the task parameter. The sensing and perception module provides information suitable for safe and accurate motion planning to the Robot Agent Node. It also helps the mapping the structure of the manufacturing shop floor for the components involved in navigation.

For the case study, the cyber physical middleware was connected to the simulation for the optimization purpose, which is also linked to the Enterprise Resource Planning (ERP) system through data management node. The production planning and scheduling data from ERP feeds to the simulation to carry out the sensitivity analysis and then to figure out the best optimize solution for the whole production process.

The input parameters such as location, transportation time and loading & unloading of mobile robots were captured through sensors. The Sensor Agent Node (SAN) module was linked to the Raspberry Pi 3 device, which was connected to the infrared sensors. A 3D printed packet was made to house the Raspberry Pi and the sensor. SAN modules were added to the routes of the mobile robots, precisely at the loading and unloading area for robots. When robots passed through, they detect the robot and crates (red boxes), send signals, and time stamp was recorded that can be observed on Human Machine Interface (HMI).

For mobile robots testing, first, the mapping was done on the designated routes by moving them around the routes with joysticks and then moving it to a starting point. After they could move anywhere that has been scanned. In the later stage, LiDAR sensors were installed on the robots that help to scan the surrounding and allows to create a map for the mapping purpose. Moreover, it facilitates to identify objects in their path like humans so they can stop. Robot Agent Node (RAN) was linked to robots so while moving around a robot sends its location data in real-time to the IoT platform, which is then displayed to the user via HMI.

Six routes were tested in the production facility, tested routes can be depicted in Fig. 6. Data about timings and the number of boxes transferred were observed that used later for the KPIs estimation.

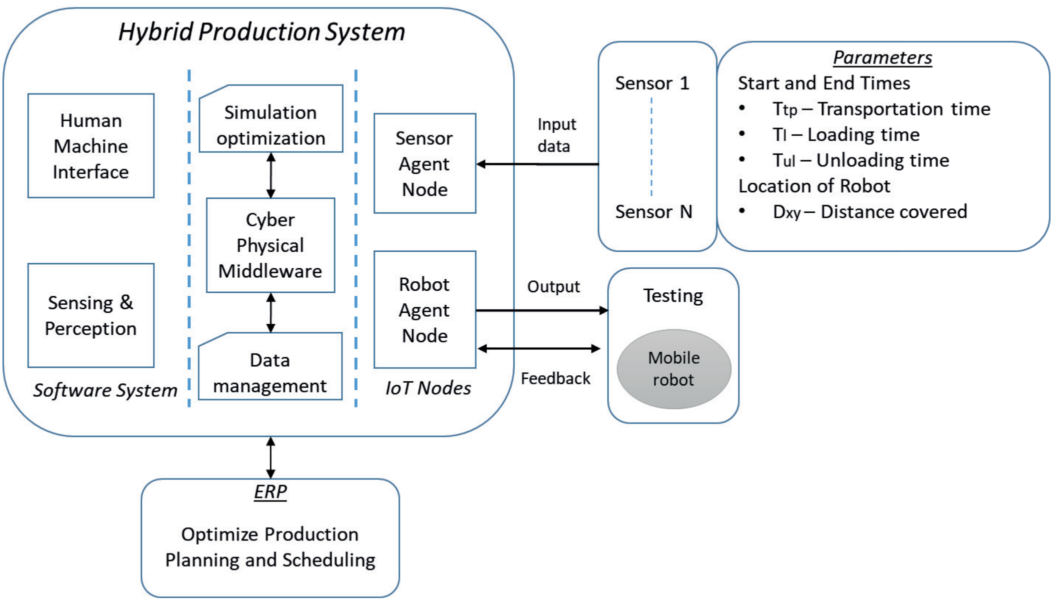

Fig. 5. Communication of entities in the factory environment (implementation of scenario)

Results of virtual and real scenarios for the automation of the intralogistics process via mobile robots were compared and presented in table 1. The observations were evaluated based on the target KPIs and positive changes were noted. The KPI-s implemented can be utilized for further optimization of the intralogistics process based on working group long time experience in engineering optimization [26].

Fig. 6. Experimental study in the factory environment

Table 1. Results based on the defined KPIs

KPI	Current Scenario (manual)	Virtual Scenario (automated)	Real Scenario (automated)	Estimated improvement
P1: Defects	Irregularities existed due to the messy corridors (routes) with random boxes (crates)	Irregularities did not exist as in the simulation the designated routes were clearly defined for robots	Irregularities were mitigated as the implementation of robots in a real environment leads to neat and clean routes.	10% reduction in existing transportation defects
P2: On-time delivery	Insufficient amount of boxes at the right time and at the right place. High waiting time at production lines	Simulation enables to plan the number of boxes at right time and place. For 12 hours simulation run with 3 robots, minor waiting time was overserved.	On-time deliveries of empty red boxes were improved as robots connected to the IoT platform, communication between them facilitate the availability of empty boxes at the right time and at the right place.	5% increase in on-time delivery
P3: Inventory turnover	Inadequate inventory turnover due to the lack of boxes. The throughput was 321 boxes per hour.	For an hour simulation run in the virtual setup of the same scale, throughput was 336 boxes.	Sensors data and controlled planning of robots enabled to improve inventory turnover.	5% increase in inventory turnover
P4: Labour Cost	Manual transportation incurs cost, when human labour realized fatigue due to repetitive activities.	Enables effective planning to allocate the workers and robots for the right and productive job.	The proper planned implementation of robots leads to a reduction in operating transportation costs. As the number of logistic workers decreased.	15% reduction in the labour cost

4. CONCLUSION

The proposed conceptual model is a contribution to evaluate the automation of the intra-logistics process and to implement mobile robots for production logistics. This work presents how to automate a production logistics process in a harmonized way, which starts with idea generation, validation through 3D simulation and visualization, followed verification by an experimental study in the real environment. The test case ensured the effective use of 3D simulation and visualization helped to reduce the installation time of robots. With the defined KPIs analysis and experimental study, it is technically feasible to use mobile robots for intralogistics, and it may enhance the proactive decision making as well. Moreover, the industrial internet of technologies helps to implement and control the autonomous mobile robots efficiently. Applied conceptual model improved the case company indoor logistics by reducing waiting time in production, the increment of on-time delivery, and decreasing the defects during the transportation process. Mobile robots provide more flexibility and a better possibility to make investments in stages according to increases in required production capacity. The proposed model can be replicated in the future to other companies that are dealing with similar business processes and production.

ACKNOWLEDGEMENTS

INTERREG project VIR19004 Innovation Framework for Challenge Oriented Intelligent Manufacturing (INforM); H2020 program project VE19030 Autonomous Mobile Robot for intralogistics at Kulinaaria OÜ; the Estonian Centre of Excellence in Zero Energy and Resource Efficient Smart Buildings and Districts, ZEBE, grant TK146 funded by the European Regional Development Fund; and the Estonian Research Core Infrastructures Roadmap project TT2 Smart Industry Centre (SmartIC).

REFERENCES

[1] GUNAL M.M., 2019, *Simulation for Industry 4.0: Past, Present, and Future*, Springer.

[2] ERBOZ G., 2017, *How to Define Industry 4.0: Main Pillars of Industry 4.0*, 7th International Conference on Management, Nitra, Slovakia.

[3] CLAUSEN U., LANGKAU S., KREUZ F., 2019, *Advances in Production, Logistics and Traffic*, Proceedings of 4th Interdisciplinary Conference on Production Logistics and Traffic, Springer.

[4] VENKATAPATHY A.K., BAYHAN H., ZEIDLER F., HOMPEL M., 2017, *Human Machine Synergies in Intra-Logistics: Creating a Hybrid Network for Research and Technologies*, Proceedings of the Federated Conference on Computer Science and Information Systems, 1065–1068.

[5] MASIK S., SCHULZE T., RAAB M., LEMESSI M., 2016, *Comprehensive 3D Visualization of Simulated Processes in Virtual Factories*, International Conf. Modeling, Sim. and Vis. Methods, 50–56.

[6] MAHMOOD K., KARAULOVA T., OTTO T., SHEVTSHENKO E., 2019, *Development of Cyber-Physical Production Systems Based on Modelling Technologies*, Proceedings of the Estonian Academy of Sciences, 68, 348–355.

[7] MÖRTHA O., EMMANOUILIDIS C., HAFNER M., SCHADLER M., 2020, *Cyber-Physical Systems for Performance Monitoring in Production Intralogistics,* J. of Computers & Industrial Eng., 142, 1–10.

[8] MAHMOOD K., KARAULOVA T., OTTO T., SHEVTSHENKO E., 2017, *Performance Analysis of a Flexible Manufacturing System*, Procedia CIRP, 63, 424–429.

[9] PAAVEL M., KARJUST K., MAJAK J., 2017, *PLM Maturity Model Development and Implementation in SME*, Procedia CIRP, 63, 651– 657.

[10] FRAGAPANE G., IVANOV D., PERON M., SGARBOSSA F., STRANDHAGEN J.O., 2020, *Increasing Flexibility and Productivity in Industry 4.0 Production Networks with Autonomous Mobile Robots and Smart Intralogistics*, Annals of Operations Research, Springer.
[11] SULE D.R., 2019, *Manufacturing Facilities: Location, Planning, and Design*, Boca Raton, CRC Press.
[12] MOSALLAEIPOUR S., NEJAD M.G., SHAVARANI S.M., NAZERIAN R., 2018, *Mobile Robot Scheduling for Cycle Time Optimization in Flow-Shop Cells, a Case Study*, Production Engineering, 12, 83–94.
[13] KUTS V., TAHEMAA T., OTTO T., SARKANS M., LEND H., 2016, *Robot Manipulator Usage for Measurement in Production Areas,* Journal of Machine Engineering, 16/1, 57–67.
[14] KANGRU T., RIIVES J., OTTO T., KUTS V., MOOR M., 2020, *Optimisation of Decision-Making Process in Industrial Robot Selection*, Journal of Machine Engineering, 20/1, 70–81.
[15] MAHMOOD K., LANZ M., TOIVONEN V., OTTO T., 2018, *A Performance Evaluation Concept for Production Systems in an SME Network*, Procedia CIRP, 72, 603–608.
[16] WURLLA C., FRITZB T., HERMANNB Y., HOLLNAICHERB D., 2018, *Production Logistics with Mobile Robots*, ISR, 50th International Symposium on Robotics, 213–218.
[17] MICHALOS G., KOUSI N., MAKRIS S., CHRYSSOLOURIS G., 2016, *Performance Assessment of Production Systems with Mobile Robots*, Procedia CIRP, 41, 195–200.
[18] FISCHER M., RENKEN H., LAROQUE C., SCHAUMANN G., DANGELMAIER W., 2010, *Automated 3D-Motion Planning for Ramps and Stairs in Intra-Logistics Material Flow Simulations*, Proceedings of the 2010 Winter Simulation Conference, 1648–1660.
[19] SCHOLZ M., et al., 2016, *Integrating Intralogistics into Resource Efficiency Oriented Learning Factories*, Procedia CIRP, 54, 239–244.
[20] NIELSEN I., DANG Q., BOCEWICZ G., BANASZAK Z., 2017, *A Methodology for Implementation of Mobile Robot in Adaptive Manufacturing Environments*, Journal of Intelligent Manufacturing, 28, 1171–1188.
[21] KAGANSKI S., MAJAK J., KARJUST K., TOOMPALU S., 2017, *Implementation of Key Performance Indicators Selection Model as Part of the Enterprise Analysis Model*, Procedia CIRP, 63, 283−288.
[22] KAGANSKI S., MAJAK J., KARJUST K., 2018, *Fuzzy AHP as a Tool for Prioritization of Key Performance Indicators,* Procedia CIRP, 72, 603–608.
[23] VISUAL COMPONENTS PREMIUM 4.2, https://www.visualcomponents.com/, (accessed 15 March 2020).
[24] SNATKIN A., EISKOP T., KARJUST K., MAJAK J., 2015, *Production Monitoring System Development and Modification*, Proceedings of the Estonian Academy of Sciences, 64, 567−580.
[25] HERRANEN H., KUUSIK A., SAAR T., REIDLA M., LAND R., MÄRTENS O., MAJAK J., 2014, *Acceleration Data Acquisition and Processing System for Structural Health Monitoring*, Proceedings of the IEEE International Workshop on Metrology for Aerospace, 244−249.
[26] MAJAK J., POHLAK M., 2010, *Optimal Material Orientation of Linear and Non-Linear Elastic 3D Anisotropic Materials*, Meccanica, 45/5, 671−680.

Appendix 3

Publication III

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Simulation based Performance Analysis of Production Intralogistics

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Abstract. Production planning and scheduling rely heavily on the efficient operations of production logistics and material handling equipment. Industry 4.0 technologies such as Internet of Things (IoT), Digital Twins, and Artificial Intelligence (AI) can be applied to production logistics in terms of autonomous mobile robots that facilitate to increase the flexibility and productivity of the whole production site. However, before the implementation of an automated production logistics systems, its feasibility must be analysed. This paper describes a simulation-based approach, including the definition of and comparative analysis of Key Performance Indicators (KPIs), to analyse the performance of production intralogistics applied to a selected use case. The presented approach offers a proof of concept on the basis of which decision-makers can implement mobile robots for intralogistics in their own production environments.

1. Introduction

In the scope of production management, the performance of activities such as obtaining raw materials to delivering finished goods to customers, need to be jointly studied and analysed. These activities are highly interconnected, and the analysis of the performance of those activities can help optimize manufacturing and logistics operations. The improvement of production intralogistics – the internal transportation of goods within a given manufacturing facility – has a major impact on the production efficiency of the whole site. As such, the requirement to optimize internal logistics systems in terms of operational performance, throughput and sustainability arises [1]. Although automation contributes a lot to business value creation and has already been to some extent introduced into the intralogistics of manufacturing facilities (e.g. conveyors, fork-lifters and pallet trucks), the aforementioned equipment allows only for a low degree of flexibility, whilst other tasks, such as loading & unloading, and the authorization of goods, are still mainly performed manually [2]. High level automation, such as the introduction of Autonomous Mobile Robots (AMR) into the intralogistics of the facility, offers a more flexible solution that can lead to a more efficient process of transportation.

Whilst intralogistics automation promises many benefits, any change within the production site introduces new challenges. For example, to ensure a smooth transition into the new workflow, a thorough change management course for line operators is recommended to be planned and carried out. Moreover, internal logistics systems are highly complex, with the deployment of AMRs requiring a thorough preliminary study and analysis. Therefore, the method of simulation and 3D visualization can be used to analyse and verify the change. Simulation modelling, paired with the Digital Twin concept and the setup of KPI (Key Performance Indicator) targets, has become a staple framework in operations management today, for the insights gained facilitate better decision-making in terms of financial, time oriented, material and energy savings, as well as the ability to streamline the process activities [3].

2. Literature Review

For the literature review, state-of-the-art articles relevant to the field of this study were analysed. Topics include the automation of production intralogistics through AMRs, the significance of simulation modelling and 3D visualization as decision-making tools, and a brief explanation of relevant Key Performance Indicators. Moreover, similar studies and related approaches are referred to in this section.

2.1. AMR in Intralogistics

Automation and the application of Internet of Things (IoT) have become widely associated with areas such as production, logistics and transportation. From the other side IoT applications in production and logistics should be seamlessly integrated into companies Manufacturing Engineering Systems (MES) [4]. AMRs for factory floor logistics persuade the smart factory concept with disruptive technologies such as Artificial Intelligence (AI), simulation and Digital Twin [5]. The use of AMRs as a type of material handling equipment creates a more ergonomic workspace for the production floor employees. Furthermore, proper deployment of AMRs may lead to an increase of production capacity and flexibility, while reducing transportation defects. Other automated solutions for factory logistics, such as conveyors, forklifts, pallet trucks, and automated guided vehicles, do not offer the same level of flexibility in terms of routing. In contrast, AMRs can be reprogrammed to be used in different applications, reacting to different data inputs. They are smaller in size and more agile than traditional automated guided vehicles; as such, they can access the production area more efficiently [6]. However, the implementation of AMRs for production intralogistics needs to be justified and verified before the physical set-up on the production floor.

2.2. Simulation Modelling and 3D Visualization

Simulation modelling is the creation of a digital model of a real-world system. Various what-if scenarios can be tested on a valid digital representation of a system to analyse, optimize, and predict the performance of processes based on set parameters [7]. After thorough experimentation in this risk-free environment, an optimal system configuration can be found and carried over into the real world. Potential problems and bottlenecks are discovered and reacted upon early in the process, thus leading to the improvement of set KPIs [8]. 3D visualization is an essential tool used to validate the simulation models´ feasibility by taking the geometry of the facility, line or process into account. 2D simulation, in comparison, offers only a low level of visual commissioning. The usage of Industrial Virtual Reality (IVR)-based 3D visualizations, which can be adapted to simulated 3D assembly layouts, product models, and process flows, may prove to be beneficial in such cases [9]. In this study, a production floor was simulated in a 3D simulation software; the assembly steps, including the mechanisms and tools on the factory floor were modelled, and the changes of the location of AMRs were analysed.

2.3. KPIs for Production Intralogistics

Performance indicators or KPIs aim to deliver information needed for the performance analysis of manufacturing operations, Intralogistics come under the discipline of operations management, and as a result, KPIs related to manufacturing operations are appropriate to production intralogistics as well, as defined in the ISO 22400 family of standards. The standard classifies KPIs based on their purpose of use, such as performance that can be measured in terms of cost, time, quality, flexibility and sustainability. Likewise, they are applicable to different types of operations, such as production, material handling, quality assurance, maintenance, and so on. [10]. Performance indicators not only showcase what has happened; they also indicate what will happen, as reactive steps will be taken by decision-makers to combat any weaknesses represented in the KPIs [11].

In this study, KPIs like *utilization*, *throughput*, and *cost* of AMRs, as well as transportation *defects* were chosen. The paper proposes a 3D simulation-based approach to analyse the performance of the production intralogistics process, though the suggested approach can be implemented to other processes as well. Several other research papers addressed the topics of intralogistics automation and the deployment of mobile robots for transportation on the factory floor [5], [12], [13]. The value of this study lies in the simplicity of the synchronized analysis approach, compared to the more difficult to construct and adopt procedures described in the aforementioned papers.

3. Simulation-based Approach for Analysis

The continuous 4-step approach (see figure 1) was adopted through the comprehensive literature review. The case study technique was used as a research method, and a use-case is introduced to validate the relevancy of the proposed approach.

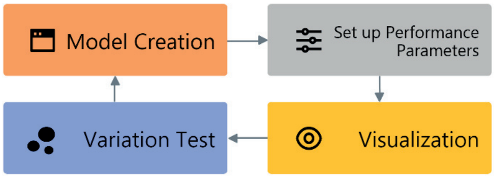


Figure 1. Simulation-based approach to analyse the performance of production intralogistics.

3.1. Model Creation

Creation of the model, a fundamental step in simulation-based analysis, facilitates to capture and describe the problem properly. A model is created by mapping the real environment to the virtual one through a specified computer-based application. A model should grasp and reveal the dynamics of a process such as the occurring of events, changes in activity timing, and resources´ state. Model parametrization also includes the selection of components (entities, source and sink, resources, etc.) relevant to the specific problem statement and system.

3.2. Performance Parameters

The acquisition of data related to the target process or system is crucial for the setup of the desired KPIs in this second step. Process parameter data, such as system specifications, input variables, and process performance metrics, are needed for the analysis. The aforementioned indicators numerically describe the behaviour of the resources, as well as activities' performance. Despite a wide selection of performance metrics being presented in various literature, KPIs must be selected depending on the underlying strategies of the company, for only then can the simulation model be built in response to the specific problem statement of the organization. For the intralogistics performance analysis and the objective of the test case, we incorporated *throughput*, *utilization*, *cost* and *defects* of the transportation activity as KPIs for the simulation analysis. Further details can be found in table 1.

Table 1. KPIs selected for this study.

KPI	Formula	Description
Throughput	$Throughput\ (R) = \frac{Average\ Inventory\ (I)}{Average\ Flow\ Time\ (T)}$	Shows the number of products transferred by an AMR from one station to another per unit time
Utilization	$Utilization = \frac{Task\ Performing\ Time}{Total\ Working\ Time} \times 100$	The percentage time that an AMR performs tasks out of the total working time or a shift duration
Cost	$Cost = Initial\ Investment + Operating\ Cost$	Shows the monetary impact of AMR in monetary terms
Defects	$Defects = \frac{Number\ of\ irregulaities}{Number\ of\ transportations} \times 100$	Expressed by irregularities in the transportation process (wrong number of goods, wrong type of goods, wrong destination)

3.3. Visualization

The exact-scale digital model of the production floor in 3D verifies the work of the real system, ensuring that the created model behaves as intended. 3D simulation assists users to visualize staff, equipment, building facility, and other items and processes in the virtual environment. The verification can be performed by providing real input data to the model and comparing the results with historical data.

Visualization also represents processing data in the form of a dashboard which helps to determine between strategic alternatives.

3.4. Variation Test
In this step, the simulation model can be allowed to test several tactical variations and scenarios that capture uncertainty. Sensitivity Analysis and Parameter Variation experiments are commonly used to reveal the effect of randomness and parameter change to the simulation model's behaviour.

4. Case Study
The proposed simulation-based approach was applied to the intralogistics process of a chemical manufacturer which produces detergents and hand sanitizer. The manually operated transportation of goods is a key operation in the production facility. Due to the high demand of products and, thus, the subsequent increase of production capacity and flexibility, the company decided to analyse and improve the intralogistics process with the intention to automate the production floor logistics by implementing AMRs. This solution is expected to reduce the transportation time and ultimately increase the process productivity, as well as cut down on workers' fatigue. The studied production facility consists of four production lines that fill empty bottles (in containers) of different sizes with liquid, label and cap them. The intralogistics related activities, planned to be executed on four different stations with the help of an AMR, are as follows:
1. Loading of products (empty bottles) in ***warehouse*** and transportation to production line
2. Unloading of empty bottles at the start of ***production line***
3. Loading of filled bottles at the end of ***production line*** and transportation to finished goods area
4. Unloading of filled bottles in ***Finished Goods*** (FG) area and moving back to the Warehouse (WH)

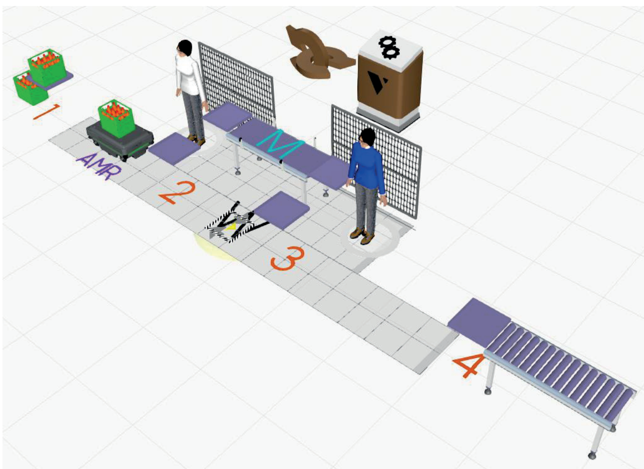


Figure 2. Simulation model of a single production line with AMR.

The 3D simulation models of the use case were created and analysed in Visual Components 4.2, a 3D manufacturing simulation software. The physical setup of the production lines and routes mapping of the AMR were constructed on the basis of full-scale production layout. Figure 2 gives a concise view and a single production line simulation model, where the intralogistics activities were marked and executed as defined above with the corresponding numbers. Figure 3 is a holistic view of the production facility and illustrates the transportation of goods using the AMR following the route WH → Production → FG → WH. The movement of the AMR was mapped and analysed during the simulation, with the green-coloured marking showing the movement of the AMR in the production area, the red-coloured one - to and from the FG area, and the yellow-coloured route – to WH and from WH.

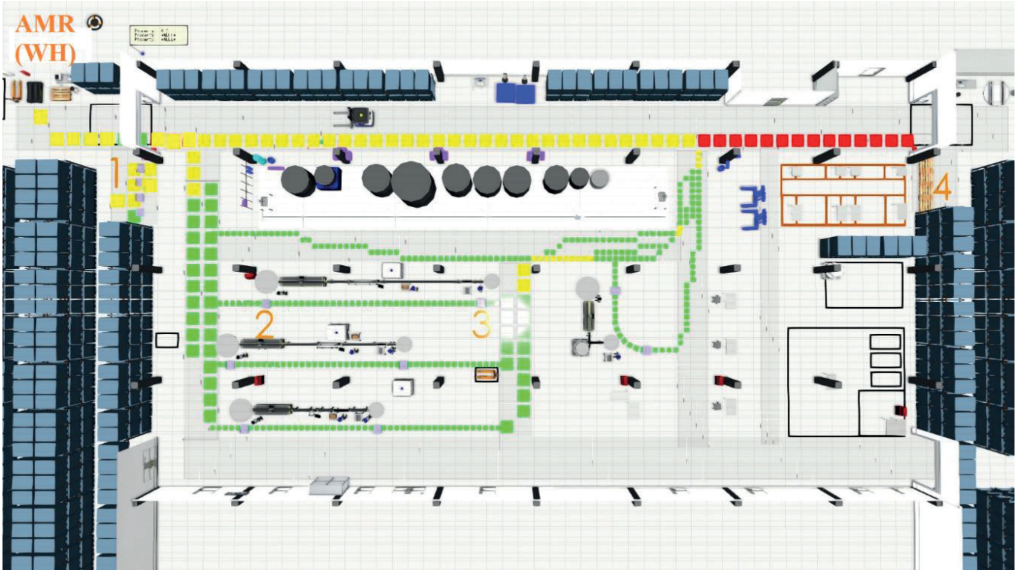
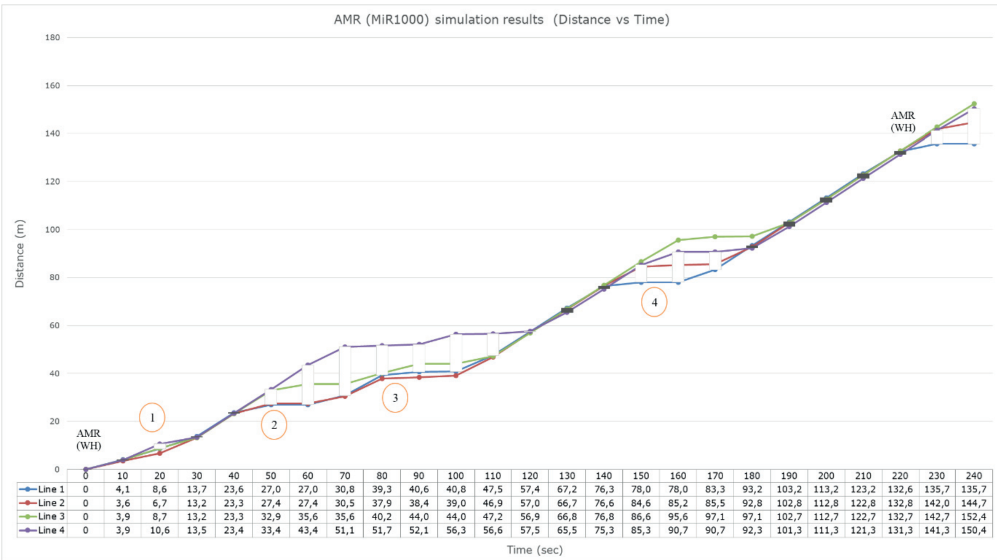


Figure 3. Detailed simulation model of the production facility (top-view).



	0	10	20	30	40	50	60	70	80	90	100	110
Line 1	0	4,1	8,6	13,7	23,6	27,0	27,0	30,8	39,3	40,6	40,8	47,5
Line 2	0	3,6	6,7	13,2	23,3	27,4	27,4	30,5	37,9	38,4	39,0	46,9
Line 3	0	3,9	8,7	13,2	23,3	32,9	35,6	35,6	40,2	44,0	44,0	47,2
Line 4	0	3,9	10,6	13,5	23,4	33,4	43,4	51,1	51,7	52,1	56,3	56,6

	120	130	140	150	160	170	180	190	200	210	220	230	240
Line 1	57,4	67,2	76,3	78,0	78,0	83,3	93,2	103,2	113,2	123,2	132,6	135,7	135,7
Line 2	57,0	66,7	76,6	84,6	85,2	85,5	92,8	102,8	112,8	122,8	132,8	142,0	144,7
Line 3	56,9	66,8	76,8	86,6	95,6	97,1	97,1	102,7	112,7	122,7	132,7	142,7	152,4
Line 4	57,5	65,5	75,3	85,3	90,7	90,7	92,3	101,3	111,3	121,3	131,3	141,3	150,4

Figure 4: Time versus distance graph of an AMR (simulation outcome).

The results of the simulation analysis can be observed in figure 4. The graph, showing the time spent and distance covered by the AMR, helps to perceive the idleness and busyness of the robot. One AMR was used to feed and serve four production lines. For the 8-hour simulation run, performance metrics such as throughput and utilization were determined. By introducing variations in the simulation model (like the number of AMRs needed for the current production capacity), the effect of an AMR implementation to the transportation cost and defects was observed. The impact of the change, i.e. the automation of the production intralogistics operation, was monitored through previously defined KPIs; the results are shown in table 2. The deployment of an AMR shows a positive impact on every KPI.

Table 2. KPI observations of current real-world and simulated scenarios.

KPIs	Current Scenario (Manual Labor)	Automated Scenario (AMR - Simulated)	Remarks
Throughput	11 pallets per shift (8 hours)	11 pallets per shift (8 hours)	Same throughput, but AMR more flexible than manual process **(+ve)**
Utilization	Fully loaded	Half-loaded	Use of AMR → extra capacity to feed/serve more than four lines **(+ve)**
Cost	Manual transportation costs	Enables effective (human & robot) resource allocation	Use of AMR → less logistics employees → reduced transportation costs **(+ve)**
Defects	Irregularities due to disorganized corridors	Irregularities did not exist thanks to designated routes for AMR	Use of AMR → neat and clean routes → less irregularities **(+ve)**

5. Conclusion

The proposed simulation-based approach is intended to help analyse the feasibility of automation of intralogistics processes and the implementation of AMRs in production logistics. Due to the possibility of achieving a high level of accuracy in the representation of a real production facility in 3D modelling and simulation software, the authors of this study recommend using the aforementioned Industry 4.0 tools as part of the decision-making workflow when automating intralogistics processes. The case study ensured the effective use of 3D simulation and visualization which helped to reduce the installation time of AMRs and analyse the production capacity to figure out the number of AMRs needed to fulfil the current capacity requirement. Moreover, with the defined KPI analysis, it is technically feasible to use AMRs for intralogistics, and it may enhance the proactive decision making as well. Mobile robots are flexible tools which can be applied in different use cases as needed and can be introduced to a production facility stage-wise, first testing a solution with just one AMR, and then gradually increasing their number per required capacity. The simulation-based approach can be replicated in other companies in the future, especially those that are dealing with similar business processes and production environments.

6. References

[1] Mörth O, Emmanouilidis C, Hafner N and Schadler M, 2020, Cyber-physical systems for performance monitoring in production intralogistics*, J. of Computers & Industrial Engg*., vol. 142, pp. 1-10.
[2] Granlund A, and Wiktorsson M, 2014, Automation in internal logistics: Strategies and operational challenges. *International Journal of Logistics Systems and Management*, 18(4), 538–558.
[3] Mahmood K, Karaulova T, Otto T and Shevtshenko E, 2017, Performance Analysis of a Flexible Manufacturing System, *Procedia CIRP*, vol. 63, 424 – 429.
[4] Riives, J.; Karjust, K.; Küttner, R.; Lemmik, R.; Koov, K.; Lavin, J. (2012). Software development platform for integrated manufacturing engineering system. *Proceedings of the 8th International Conference of DAAAM Baltic Industrial Engineering, Tallinn, Estonia*, 19-21 april 2012. Ed. Otto, T., pp. 555−560.
[5] Klumpp M, *et al*, 2019, Production logistics and human-computer interaction—state-of-the-art, challenges and requirements for the future, *The International Journal of Advanced Manufacturing Technology*, vol.105, 3691–3709
[6] Fragapane G, *et al*, 2020, Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics, *Annals of Operations Research*, Springer.
[7] Laguna M and Marklund J, 2019, *Business Process Modeling, Simulation and Design*, 3rd Ed, CRC Press,
[8] Straka M, *et al*, 2017, Application of extendsim for improvement of production logistics' efficiency, *International Journal of Simulation Modelling*, vol.16 (3), 422-434.
[9] Masteamssik S, Schulze T, Raab M and Lemessi M, 2016, Comprehensive 3D Visualization of Simulated Processes in Virtual Factories, *International Conf. Modeling, Sim. and Vis. Methods*, pp. 50-56.
[10] Hwang G, Lee J, Park J and Chang T, 2017, Developing performance measurement system for Internet of Things and smart factory environment, *International Journal of Production Research*, vol. 55, 2590–2602.
[11] Mahmood K, Lanz M, Toivonen V and Otto T, 2018, A Performance Evaluation Concept for Production Systems in an SME Network, *Procedia CIRP*, vol. 72, 603 – 608.
[12] Michalos G, Kousi N, Makris S and Chryssolouris G, 2016, Performance assessment of production systems with mobile robots, *Procedia CIRP*, vol. 41, 195 – 200.
[13] Fischer M, *et al*, 2010, Automated 3D-Motion Planning for Ramps and Stairs in Intra-Logistics Material Flow Simulations, *Proceedings of the 2010 Winter Simulation Conference*, pp. 1648-1660.

Appendix 4

Publication IV

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OPTIMIZATION OF PRODUCTION LOGISTICS

Autonomous mobile robots for production logistics: a process optimization model modification

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Abstract. Digital solutions have become increasingly important for manufacturing companies to increase their productivity, effectiveness, and competitiveness in a global market, which demands low prices, high quality, and fast delivery times. In order to improve production efficiency, it is also necessary to optimize transportation activities in the production floor via digitization and automation of those processes. Many companies have already used or are planning to use autonomous mobile robots (AMR) to manage production logistics more effectively. The rapid development of the Internet of Things (IoT) and the advanced hardware and software of AMR allow them to perform autonomous tasks in dynamic environments, where they can communicate and independently coordinate with other resources, such as machines and systems, and thus decentralize the decision-making steps of manufacturing processes. Decentralized decision making allows the manufacturing system to dynamically adapt to changes in the system state and environment. Such developments have affected traditional planning and control methods and decision-making processes, but they also require the software and embedded artificial intelligence (AI) algorithms to be more capable of executing these decisions. In this study, we describe how to use a 3D virtual factory concept to integrate an AMR system with AI functionality into the production logistics of the food industry. The paper presents an approach to analyze the performance of AMR in the transportation of goods on the manufacturing plant floor, based on the creation and simulation of the 3D layout, the monitoring of key performance indicators (KPI), and the use of AI for proactive decision making in production planning. A case study of the food industry demonstrates the relevance and feasibility of the proposed approach.

Keywords: autonomous mobile robot, production logistics, Internet of Things, virtual factory, artificial intelligence.

1. INTRODUCTION

Nowadays, the main paradigm in manufacturing is based on the reconfigurable manufacturing and Industry 5.0 (moving towards Industry 6.0), in alignment with the goals of the EU Green Deal and the digital and green twin transition. Reconfigurable manufacturing systems (RMS) is an approach in manufacturing, which is designed for a rapid adjustment of production capacity and functionality, in response to new market conditions. Flexible manufacturing systems with integrated autonomous mobile robots (AMR) make it possible to produce a variety of products on the same system. The objective is to provide the required functionality and capacity precisely when it is needed.

The AMR have been introduced in various fields of modern industry to increase efficiency, productivity, and safe transport of goods and materials, and they perform various predetermined transport tasks without direct operator intervention [1]. Usually, the manufacturers of such AMR systems also have control software, which enables various transport missions to be performed in automatic mode and via a human-machine interface (HMI) according to predetermined routes [2]. The constant increase of the use of AMR systems will create various problems such as deadlocks and conflicts between system components,

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which cause a decrease in the efficiency of these systems [3]. The complexity of managing and controlling these AMR systems is an important factor, which limits their implementation in a small or medium-sized company and inhibits their effectiveness in fulfilling transport tasks. In addition, most previous studies related to the introduction of automated production logistics have focused on various robots' central control and optimization; however, according to our understanding, no sufficiently researched methods exist for each robot to plan its activities independently. Only in recent years, more research has begun on decentralized control systems, where each robot is assigned a different task in order to optimize the percentage of on-time assembly and delivery of goods in various social situations [4]. To analyze the feasibility and efficiency of such AMR systems, a case study and advanced simulation model based on 3D visualization, simulation, the use of IoT sensors, and experimental research should be used in advance [5] to monitor the existing key performance indicators (KPI) in the real work conditions [6,7]. It is a holistic method that allows for a more accurate assessment of the AMR solution design and its impact (KPI) before implementing it in the company's production logistics. Automation of manufacturing processes using robots helps to reduce Lean waste [8] and thus increase productivity through Lean methods [9], supporting the adoption of AMR in the factory. Recently, smart artificial intelligence (AI) based algorithms, such as ant colony optimization [10], genetic algorithm [11], A* algorithm [12], simulated annealing [13], etc., have been proven to be effective tools for mobile robot trajectory planning. Global optimization of factory- and warehouse-based AMR is too computationally complex and time consuming to account for dynamically changing obstacles in transportation tasks. In a dynamic environment, global trajectory planning can result in potential collisions with other objects because the algorithm does not adapt to changes in the environment [14] or the AMR must make a sudden stop. However, the problem with local trajectory planning methods, such as the artificial potential field method, is that they get stuck in a local minimum and cause irregularities [15] that increase energy consumption.

Combinatorial and AI-based algorithms are investigated in this work, based on the long-term experience of the authors' working group in the use of AI tools and methods in various engineering fields [16,17]. The case study and the advanced simulation model of production logistics gives us a good visual overview and a precise understanding of how to optimize and make the management of AMR systems more efficient and to interface them with the company's various IT systems and fleet of devices. This paper focuses on the development of configurable automated logistics solutions, including the use of AI functions and 3D simulation software to virtualize and simulate manufacturing logistics. Derived from AI-based tools, various algorithms are proposed for easy reconfiguration and planning of tasks and movement paths of mobile robots.

2. APPROACH FOR AMR PROCESS ANALYSIS AND MODIFICATION

The process for the transportation of goods by AMR on the production floor is analyzed and implemented through the approach as anticipated in our previous study [18] and illustrated in Fig. 1. Apart from the 3D simulation and experimentation of AMR, the proposed approach consists of an AI model and its testing, which facilitates proactive decision making besides simulation analysis. This approach intends to be adopted for the automation of production logistic processes using AMR. It is based on the digital mockup of a production floor and immersive 3D simulation analysis to validate the case study and advanced simulation model; moreover, the verification can be performed by implementing the case study and the advanced simulation model as an experimental testing in a physical factory environment.

There are three main phases in this approach. The first one involves conceptualization for the automation of a particular process and task, for example, generating several ideas via brainstorming activity to automate the transportation task on a production floor. The outcome of the conceptualization phase unfolds an automation scenario for the transportation process. The second phase is to create a digital mockup of that transportation process on a factory floor and conduct simulation analysis through KPI in the virtual environment. As a result of the second phase, valuable knowledge is captured and used for the

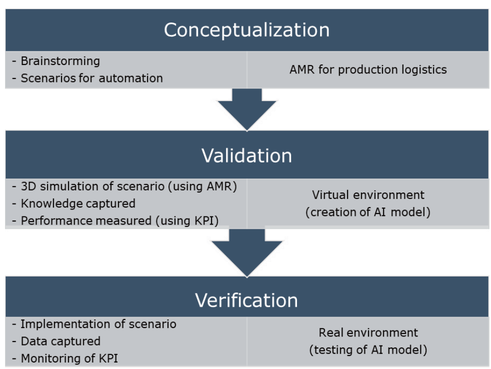

Fig. 1. Proposed approach to analyze the process of AMR for production logistics [18].

implementation of AMR in the real (physical) environment, while an AI model can also be formulated based on the simulation model. The third phase involves testing the simulation model and implementing AMR in the real environment, which serves as an experimental use case. The data about the movement of AMR, the location, and distance traveled can be collected via IoT sensors. Furthermore, the KPI can be calculated by the captured data, and they visualize the performance of AMR by integrating the data to a monitoring dashboard.

This study emphasized the construction of a process layout, simulating the AMR transportation on a production floor by using a 3D virtual environment and executing performance analysis. An AI model was also created for the route planning and optimal pathfinding of AMR. In order to realize the feasibility of the proposed approach, the case study research method was practiced.

2.1. Digital and simulation model development for the food industry use case

The 3D layout and simulation of AMR routings were constructed in the Visual Components software [19]. Different paths and movements of AMR were comprised as follows: AMR transported ten red plastic boxes with each running on different paths, which are displayed in Fig. 2.

AMR path setup and routing:

- **Paths 1–2 and 1–3:** Transportation of washed empty boxes with AMR to specific production processes (picking up red plastic boxes from buffer 1, placing them in buffer 2 and buffer 3);
- **Path 2–4:** Transportation of filled boxes (partially finished goods or finished goods) with AMR to the warehouse (picking up red plastic boxes from buffer 2 and placing them in buffer 4);
- **Path 4–5:** Transportation of dirty empty boxes with AMR to the washing area (picking up red plastic boxes from buffer 4 and placing them in buffer 5);
- **Path 6–9:** Transportation of packaging materials to intermediate warehouses (picking up cardboard boxes from warehouse 6 and placing them in intermediate warehouses 7, 8, and 9).

The paths contain various buffers, including the empty boxes area (buffer W), filled boxes area (buffer F), dirty boxes area (buffer D), and production processes buffers area for picking up and placing the goods (boxes) with AMR. A unified view of buffers for loading and unloading places with AMR is displayed in Fig. 3. The number of optimized loading and unloading places for buffers depends on the production volume and product capacity. Consequently, some buffers have one place for loading and one place for unloading, but some have two places for loading and unloading. Moreover, the buffer location numbers in Fig. 2 correspond to the loading and unloading places in Fig. 3. These two figures are associated with each other in the way that Fig. 2 shows the paths of AMR with buffer locations, while Fig. 3 represents the loading and unloading of boxes by AMR at these locations.

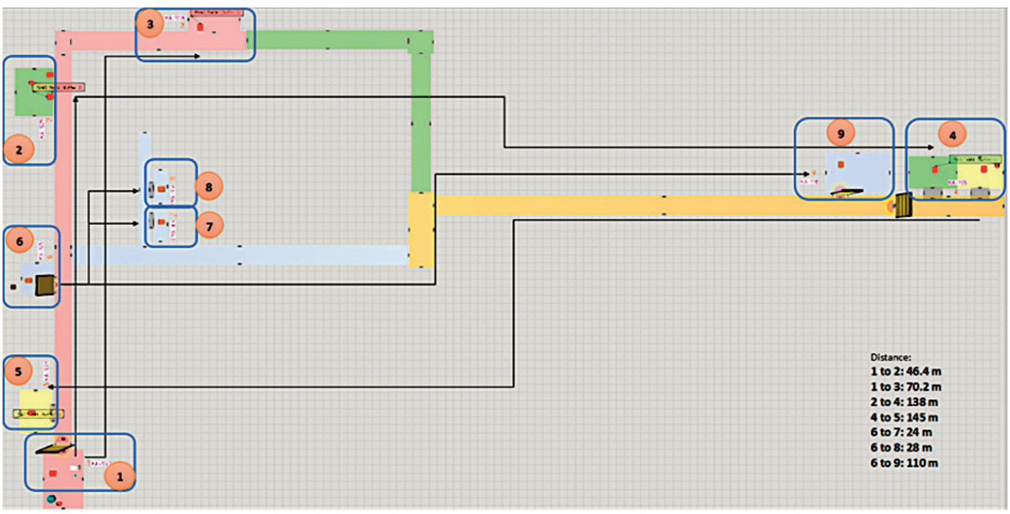

Fig. 2. AMR routing map and buffers for picking up and placing the boxes in the manufacturing area.

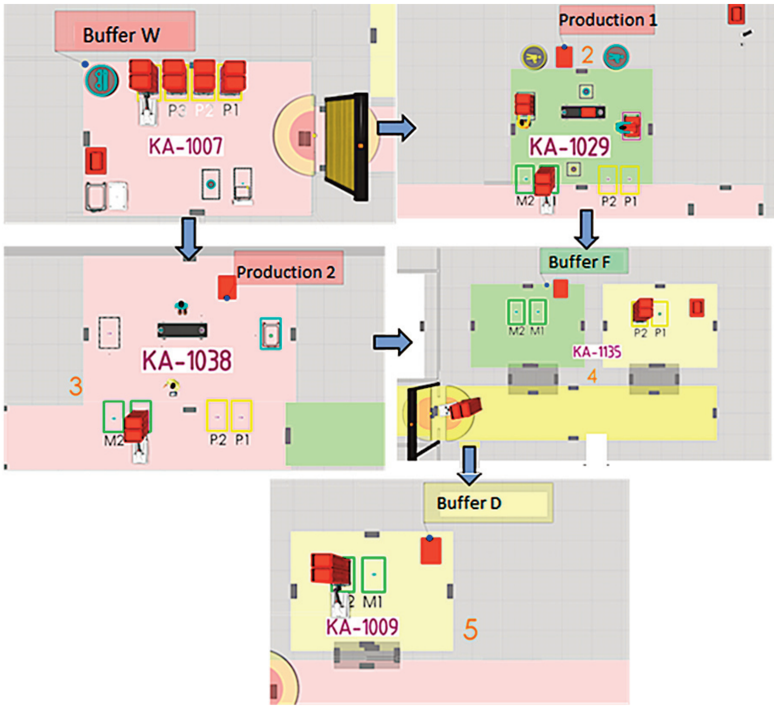

Fig. 3. AMR loading and unloading stations on the production floor.

2.2. AMR process simulation results

The KPI analyzed in the transportation process of AMR in the food industry use case are the number of transportation boxes, transportation time, and utilization. These KPI are important because they measure the efficiency and effectiveness of the AMR transportation process in the food industry. The number of transport boxes indicates how many boxes AMR can transport in a given time. Transit time measures how long it takes for AMR to deliver boxes from one point to another. Utilization shows how much of AMR's capacity is used for transport. These specifically selected KPI help to optimize the transport process, reduce costs, improve customer satisfaction, and increase productivity. These KPI are also used in the further optimization of AMR movement in the factory area. During the analysis, two scenarios were tested based on the production cycle, production capacity, and the number of shifts. The first tested scenario was with AMR speed of 1 m/s and the second one with AMR speed of 0.5 m/s. The simulation results of the two scenarios are displayed in Table 1.

Table 1. Summary of AMR simulation analysis

Performance parameter	Scenario 1: AMR speed 1 m/s	Scenario 2: AMR speed 0.5 m/s
Number of transported boxes [pcs]	400 pcs at each buffer location	400 pcs at each buffer location
Total transportation time [s]	22 140 s	35 640 s
AMR average utilization [%]	100% (continuous movement of AMR)	100% (continuous movement of AMR)
AMR pick up and place time [s]	60 s	60 s
Total AMR travel distance [m]	14 500 m	14 500 m

3. AI-BASED DECISION-MAKING SYSTEMS FOR MOBILE ROBOTS

The decision-making system proposed for the AMR is focused on the optimal path planning and safety visualization for mobile robots via introducing additional depth sensors to the work area of robots, calibrating the information feed and projections around AMR approaching the human. On the other hand, the decision-making systems are linked with the production scheduling via online information gathering from the manufacturing processes and positioning of AMR. The information flow between the mobile robot control system, the company-based enterprise resource planning (ERP) system, and the mobile robot monitoring system is displayed in Fig. 4. It is very important to integrate with the existing systems also the system efficiency control system, which helps us to optimize the existing systems and track the possible faults and less efficient components/parts.

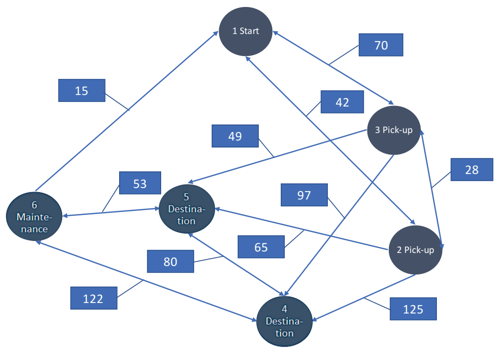

Fig. 5. AMR motion model.

3.1. Directed graph definition

Below, a directed graph with its nodes and edges is introduced. The term "node" is utilized for the starting point, loading and unloading points, and the maintenance point(s). A sensor system is set up so that information is acquired from all nodes. The same general design is applied for all nodes, but some nodes may have extra specific information (maintenance data, etc.). In Fig. 5, the directed graph is depicted showing all nodes and edges but also distances between the nodes and available moving directions. It should be noted that Fig. 5 represents a schematic graph, i.e., distances are not proportional.

The general structure of the node is the following: **Error! Reference source not found.**, node No., loading (1 – available, 0 – not available), unloading (1 – available, 0 – not available), priority.

Currently, the priority value is calculated based on the remaining time until preservation, but there are additional considerations to take into account. The problem is solved by using object-oriented programming, considering each node as an instance of the node class. Nodes provide valu-

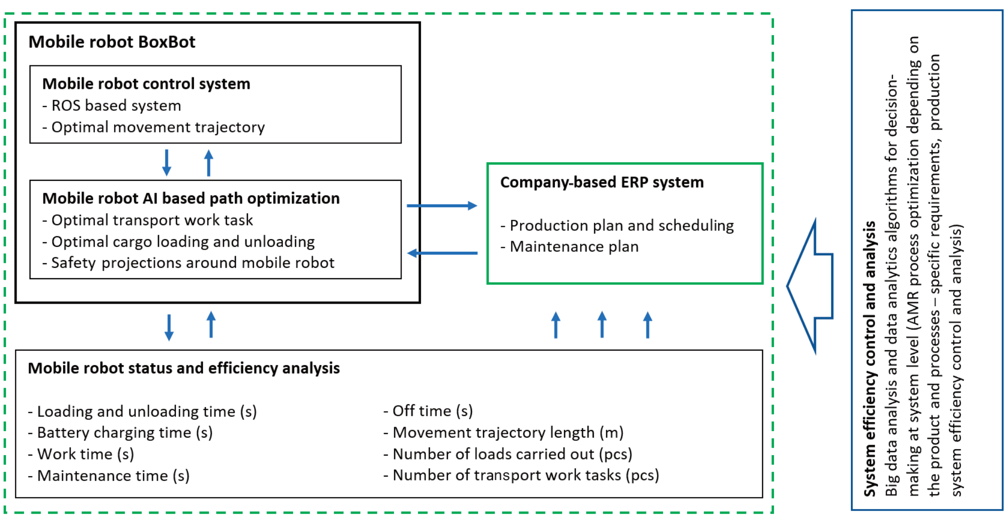

Fig. 4. General framework of the AMR data exchange.

able information for decision making and, additionally, some general information, such as all available moves between nodes together with distances, etc. The latter information is stored in a table, including node numbers and the corresponding distances. The distances can be replaced with travel times if such information is available from statistics for the current application.

3.2. Optimal path optimization

The optimization approach proposed in the current study is based on the decomposition method and has a hierarchical structure. Using the information acquired from the nodes and all other information available in the upper-level design, the loading and unloading points to be visited during the next route are determined. This process can be called a "mission". In the lower-level design, it is decided how to execute the mission, i.e., how to determine the optimal path from the start point, through the selected loading and unloading nodes, and back. The latter tasks are again divided into subtasks. The optimal paths are determined separately from the start to the loading node(s), from the loading node(s) to the unloading node(s), and from the unloading node(s) back to the starting point. Such an approach ensures the passage of all nodes of the mission. The information required for the lower-level design is the location of the nodes, the distances between nodes and the available moving directions. One can conclude that in the upper level, the nodes to be passed during the next mission are determined, while the path used is determined in the lower level.

In the case of the considered small application, several shortest-path algorithms, such as genetic algorithms, particle swarm algorithms, and ant colony algorithms, are

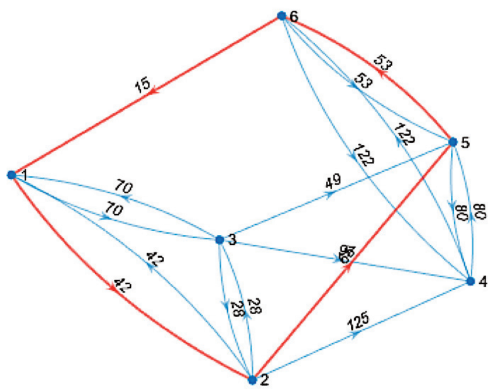

Fig. 6. The optimal path for AMR movement (mission passing loading node 2 and unloading node 5).

applicable due to a limited dataset (both the loading and unloading node arrays include two nodes). Combinatoric algorithms such as Dijkstra and Bellmann–Ford are less time consuming, based on their time complexity estimates O(E+log(N)*N) and O(N*E), respectively. As expected, the numerical tests performed in the current case study show that the population-based algorithms are significantly slower. The optimal path indicated by the red line in Fig. 6 corresponds to the route 1-2-5-6-1 and has the length of the path equal to 175 units. The most suitable optimal path algorithm (fast and simple to implement) depends on the particular problem or class of problems considered. For the problem considered, the Dijkstra algorithm was the best.

4. CONCLUSIONS

The aim of this study was to investigate how mobile robots in the food industry, which are autonomous and adaptable to different use cases, can be combined with AI functions, which control their movements and transport tasks, and with the company's existing resource planning system, which helps to optimize their work processes. To address this task, a virtual factory (VF) was created using a 2D drawing of the company's floor plan, which represented as accurate a 3D model as possible of what actually happens in the food industry. The VF simulation used the company's real production data to evaluate the suitability and usefulness of AMR in a given environment and their integration with existing processes. The proposed holistic approach using digital solutions is a quick and easy way to find a solution to a specific problem and analyze and evaluate the results based on that.

The case study and the advanced simulation model proposed in the paper create a cyber-physical environment with an integrated ERP system, a mobile robot control system as well as a VF with workstations and AI functions to help solve the problems of planning transport orders for robots. This makes it possible to test various digital solutions in advance in a VF and choose the most effective, simple, and cost-effective of them when using AI.

Applying the principles of the decentralized control system, in cooperation with the VF concept, we can create simple and understandable AI optimization models for generating AMR transport missions, which are easier for system operators to set up and manage according to the specifics of the company and the existing production plan. This innovative approach allows AMR systems to be simulated, optimized, and improved in advance to ensure easier and faster creation of these transport tasks and efficient and flexible transport of goods on the factory floor.

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REFERENCES

1. Fragapane, G., de Koster, R., Sgarbossa, F. and Strandhagen, J. O. Planning and control of autonomous mobile robots for intralogistics: literature review and research agenda. *Eur. J. Oper. Res.*, 2021, **294**(2), 405–426. https://doi.org/10.1016/j.ejor.2021.01.019
2. de Paula Ferreira, W., Armellini, F. and De Santa-Eulalia, L. A. Simulation in industry 4.0: a state-of-the-art review. *Comput. Ind. Eng.*, 2020, **149**, 106868. https://doi.org/10.1016/j.cie.2020.106868
3. De Ryck, M., Versteyhe, M. and Debrouwere, F. Automated guided vehicle systems, state-of-the-art control algorithms and techniques. *J. Manuf. Syst.*, 2020, **54**, 152–73. https://doi.org/10.1016/j.jmsy.2019.12.002
4. Warita, S. and Fujita, K. Online planning for autonomous mobile robots with different objectives in warehouse commissioning task. *Information*, 2024, **15**(3), 130. https://doi.org/10.3390/info15030130
5. Raamets, T., Karjust, K., Hermaste, A. and Mahmood, K. Planning and acquisition of real-time production data through the virtual factory in chemical industry. In *Proceedings of the ASME 2021 International Mechanical Engineering Congress and Exposition (IMECE2021), (online) USA, 1–5 November 2021.* ASME, **2B** (Advanced Manufacturing), V02BT02A017. https://doi.org/10.1115/IMECE2021-73080
6. Musthafa, M. D. A., Thamrin, N. M., Abdullah, S. A. C. and Mohamad, Z. An IoT-based production monitoring system for assembly line in manufacture. *Int. J. Integr. Eng.*, 2020, **12**(2), 38 – 45. https://doi.org/10.30880/ijie.2020.12.02.005
7. Bonci, A., Di Biase, A., Giannini, M. C., Indri, M., Monteriù, A. and Prist, M. An OSGi-based production process monitoring system for SMEs. In *Proceedings of the IECON 2022 – 48th Annual Conference of the IEEE Industrial Electronics Society, Brussels, Belgium, 17–20 October 2022.* IEEE, 2022, 1–6. https://doi.org/10.1109/IECON49645.2022.9968742
8. Karaulova, T., Andronnikov, K., Mahmood, K. and Shevtshenko, E. Lean automation for low-volume manufacturing environment. In *Proceedings of the 30th DAAAM International Symposium "Intelligent Manufacturing and Automation", Zadar, Croatia, 23–26 October 2019.* DAAAM International, Vienna, Austria, 2019, **30**(1) 0059–0068. https://doi.org/10.2507/30th.daaam.proceedings.008
9. Mahmood, K. and Shevtshenko, E. Productivity improvement by implementing Lean production approach. In *Proceedings of the 10th International Conference of DAAAM Baltic Industrial Engineering, Tallinn, Estonia, 12–13 May 2015*. TalTech, 2015, 1−7.
10. Wu, L., Huang, X., Cui, J., Liu, C. and Xiao, W. Modified adaptive ant colony optimization algorithm and its application for solving path planning of mobile robot. *Expert Syst. Appl.*, 2023, **215**, 119410. https://doi.org/10.1016/j.eswa.2022.119410
11. Chen, Y.-Q., Guo, J.-L., Yang, H., Wang, Z.-Q. and Liu, H.-L. Research on navigation of bidirectional A* algorithm based on ant colony algorithm. *J. Supercomput.*, 2021, **77**, 1958–1975. https://doi.org/10.1007/s11227-020-03303-0
12. Chong, Y., Chai, H., Li, Y., Yao, J., Xiao, G., and Guo, Y. Automatic recognition of geomagnetic suitability areas for path planning of autonomous underwater vehicles. *Mar. Geodesy*, 2021, **44**(4), 287–305. https://doi.org/10.1080/01490419.2021.1906799
13. Tlili, T. and Krichen, S. A simulated annealing-based recommender system for solving the tourist trip design problem. *Expert Syst. Appl.*, 2021, **186**, 115723. https://doi.org/10.1016/j.eswa.2021.115723
14. Szczepanski, R. and Tarczewski, T. Global path planning for mobile robot based on artificial bee colony and Dijkstra's algorithms. In *Proceedings of the 2021 IEEE 19th International Power Electronics and Motion Control Conference (PEMC), Gliwice, Poland, 25–29 April 2021.* IEEE, 2021, 724–730. https://doi.org/10.1109/PEMC48073.2021.9432570
15. Song, J., Hao, C. and Su, J. Path planning for unmanned surface vehicles based on predictive artificial potential field. *Int. J. Adv. Robot. Syst.*, 2020, **17**(2). https://doi.org/10.1177/1729881420918461
16. Pikner, H., Sell, R., Majak, J. and Karjust, K. Safety system assessment case study of automated vehicle shuttle. *Electronics*, 2022, **11**(7), 1162. https://doi.org/10.3390/electronics11071162
17. Paavel, M., Karjust, K. and Majak, J. Development of a product lifecycle management model based on the fuzzy analytic hierarchy process. *Proc. Estonian Acad. Sci.*, 2017, **66**(3), 279−286. https://doi.org/10.3176/proc.2017.3.05
18. Mahmood, K., Karjust, K. and Raamets, T. Production intralogistics automation based on 3D simulation analysis. *J. Mach. Eng.*, 2021, **21**(2),102−115. https://doi.org/10.36897/jme/137081
19. Visual Components. https://www.visualcomponents.com (accessed 2022-11-15).

Autonoomsed mobiilsed robotid tootmislogistikas: protsessi optimeerimismudeli muutmine

Tõnis Raamets, Jüri Majak, Kristo Karjust, Kashif Mahmood ja Aigar Hermaste

Digitaalsed lahendused on muutunud tootmisettevõtetele üha olulisemaks, suurendades tootlikkust, tõhusust ja konkurentsivõimet globaalsel turul, mis nõuab madalaid hindu, kõrget kvaliteeti ja kiiret tarneaega. Tootmise efektiivsuse parandamiseks tuleb optimeerida ka tootmispõrandal toimuvaid transporditegevusi protsesse digiteerides ja automatiseerides.

Paljud ettevõtted juba kasutavad või plaanivad kasutada autonoomseid mobiilseid roboteid (AMR), et hallata tootmislogistikat efektiivsemalt. Asjade interneti (IoT) ja AMRide riist- ja tarkvara kiire areng võimaldab neil sooritada autonoomseid ülesandeid dünaamilistes keskkondades, kus nad saavad suhelda ja tegevusi iseseisvalt koordineerida teiste ressurssidega, nagu masinad ja süsteemid. See võimaldab detsentraliseerida tootmisega seotud otsustusprotsessi. Detsentraliseeritud otsustamine omakorda võimaldab tootmissüsteemil dünaamiliselt kohaneda süsteemi oleku ja keskkonna muutustega. Need arengusuundumused on mõjutanud traditsioonilisi planeerimis- ja kontrollimeetodeid ning otsustusprotsesse, eeldades tarkvara ja sisseehitatud tehisintellekti (AI) algoritme, mis oleksid võimelised neid otsuseid täitma.

Selles uuringus kirjeldame, kuidas kasutada virtuaalse 3D-tehase kontseptsiooni, et integreerida AI-funktsionaalsusega AMR-süsteem toiduainetööstuse tootmislogistikasse. Artiklis esitatakse lähenemisviis AMRi jõudluse analüüsiks tootmistehase põrandal kaupade transportimisel, mis põhineb 3D-paigutuse loomisel ja simuleerimisel, peamiste tulemusnäitajate jälgimisel ning tehisintellekti kasutamisel proaktiivseks otsustamiseks tootmisplaneerimises. Toiduainetööstuse juhtumiuuring näitab väljapakutud lähenemisviisi asjakohasust ja teostatavust.

Appendix 5

Publication V

Moor, Madis; Pakkanen, Jarkko; Raamets, Tõnis; Mahmood, Kashif; Riives, Jüri (2024). Industrial Data Analytics in Manufacturing Shop Floor Level. AIP Conference Proceedings, 2989/1: Modern Materials and Manufacturing 2023, Tallinn, Estonia, 2-4 May 2023. Ed. Karjust, Kristo; Kübarsepp, Jakob. New York: AIP Publishing, #030006. DOI: 10.1063/5.0189502.

Industrial Data Analytics in Manufacturing Shop Floor Level

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Abstract. Cloud-based Services and Data Analytics (DA) in manufacturing has an extremely important role. Data itself, as a source of information and processed data for improvement. The necessity of digitalization on the shop floor enables different data sources which are key to advanced analytics. To achieve this, various sensors, programmable logic controllers (PLCs), input/output (IO) devices, etc are used. The objective is that a company controls a process or production, based on collected data, using data analytics procedures and if needed AI-based decision-making algorithms. In this article, we provide an example of how a set of production and performance data are gathered in real-time, and an operational data set is used and analyzed for improvements in the planning and execution phase. The manufacturing data model is based on specific workplace or operation and describes the activity as a part of process or involves the whole manufacturing process. The analytics model, based on key-performance indicators (KPIs), provides an opportunity to understand the situation, and to learn to be able to predict different scenarios with different variables. In this article, some examples of data analytics for performance improvement are presented.

INTRODUCTION

The last few years have been challenging for the global economy and manufacturing. Manufacturers have been struggling to recruit and retain workers in the sector. In 2019, according to Eurofound, 39% of European manufacturing enterprises reported limitations in production due to labor shortages. It is predicted by United Nations (UN) analysis that Europe will lose 95 million workers between 2015 and 2050 [1]. This is a multi-level problem with no single solution. The key is to concentrate on strategies that will improve the current situation. Firstly, to attract, engage and retain the next generation of manufacturing workers. The nature of a specialist in manufacturing has changed and will be even more. Manufacturing is currently a combination of different fields etc. automation, IT, mechanics, and electronics. This requires a high level of knowledge. The industry's priority in this ever-changing environment is to find effective methods, procedures, and measures that would allow its flexibility to change conditions [2].

Secondly, to enhance productivity by using digital tools in companies to compensate for the lack of labor. Entrepreneurs have the technological capabilities in terms of equipment and machinery, but the pressure of lack of workers is a vital problem. Using various smart sensors and digital tools, it is possible to raise the flexibility and

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efficiency of a workplace [3]. One thing is to monitor or plan processes and production by ERP or MES, another is to integrate the data back into the workplace with optimized parameters.

In this article, we discuss and present examples in terms of productivity and digital tools, stated above. The study is carried out in small and medium-sized enterprises (SMEs), in Estonia. The company is equipped with modern machinery, based on CNC controlled, etc. bending, turning, milling, and supported by industrial robots (IRs) for welding, machine tending, and packaging. Common digital tools such as ERP is used to monitor and plan production, but digital tools are not used to specify what is happening inside one workplace.

LITERATURE REVIEW

Industrial Internet

The industrial internet means digitization on an industrial scale where ICT technologies are used in sectors and places where they have not been used before. The physical world includes, for example, industrial machines and devices, their actuators, and sensors. In addition, the physical world is represented by an information network, through which data can be continuously transmitted to the digital world. The digital world is thus represented by the data itself, cloud platforms, data analytics, and algorithms. Various software and program-based services serve as the user interface of the digital world. By continuous data collecting and analysis, the systems of the physical world can be connected to a larger hyperphysical ecosystem. Through this, companies can create new operating models, products, and even more autonomous and dynamic solutions [4]. Moreover, the application of industrial internet to digitalize and evolve manufacturing systems can be perceived as Cyber-Physical Production Systems (CPPS) such systems represented a physical system in the virtual world and vice-versa. They can be developed and implemented for the purpose of autonomous decisions in manufacturing processes [5].

Cloud-based services

Cloud computing is the delivery of services such as servers, storage databases, networking, software, or analytics over the Internet. By using cloud services, users are offered faster innovations, flexible resources, and the ease of use of the different technologies. Exploiters usually pay for the services they use which helps keep the operating costs down and the infrastructure can be run more efficiently [6].

Kuzmiakova [7] has listed nine reasons why organizations are turning to cloud computing services:

- Inexpensive: it saves a lot of money as users do not have to invest in physical hardware. Users do not have to be highly trained in maintaining hardware.
- High speed: the resources needed by the system can be acquired in a shorter time.
- Back-up and restore data: when data is stored in the cloud, backups and restore tasks can be executed easily and fast.
- Automatic software integration: normally cloud integrates software automatically. The user is not required to customize and integrate the applications.
- Reliability: the cloud technologies normally update the users on any occurred alterations immediately.
- Mobility: the user only needs an internet connection to access cloud services.
- Unlimited storage capacity: in most cases, storage capacity can be extended almost limitless and monthly fees are typically very low.
- Collaboration: cloud technology allows users to communicate around the world in a secure way.
- Quick deployment: transferring the service to a cloud platform is usually easy and fast.

REST API

REST is an acronym for Representational State Transfer [8]. In the early days' SOAP (Simple Object Access Protocol) was mainly used in web services HTTP and SMTP (Simple Mail Transfer Protocol) for transferring data packages between the same or different platforms. The main difference between these two data transfer methods is that REST is a hybrid system. When SOAP supports only XML format, REST supports JSON and other formats as well. This is the main reason why REST has become the most used method for data transfer in web-based applications. REST is not a protocol; it is rather an architectural principle for managing state information [9].

API is short for Application Programming Interface. It is used to process data inside a closed system. Programmers can use these APIs to build services that use data and services from external sources. Michel [10] refers to David Orenstein who describes an API with a metaphor: Imagine that you are building a terrace on your house. You do not have a hammer though. You know your three neighbors have a hammer. You know that one of the neighbors never borrows his stuff, so he describes a closed system in this case. The other neighbor, on the other hand, always keeps the doors of his warehouse open and anyone can pick up goods from his warehouse at any time. This neighbor represents an open-source system. The third neighbor lends his tools if permission is asked first. So, he is an API system.

By separating the user interface from the server and data storage, the development of an API is improved. For example, the portability of the interface to other types of platforms is improved, the project scalability is increased, and different components can be developed independently. Projects can be easily migrated to other servers or changes can be made to the database. Therefore, the overall flexibility of the development is increased by the separation [11].

USECASE: DATA COLLECTION AND INTEGRATION

Application of Dimusa system in robot-based workplace

Dimusa is a model-based, real-time production monitoring and prediction system with optimal functionality (with custom reconfiguration options) with low investment cost and integration time. The production process analyzation model provides the opportunity to accelerate its application time, together with KPIs specification and the integration of system procedures. Advanced production monitoring and prediction system are capable of identifying variables affecting performance, such as measuring and monitoring events and situations that directly affect the reliability of production systems and processes. An efficient real-time information flow includes data collection in the system:

- the condition of the equipment,
- production data,
- order fulfillment,
- material flow,
- product quality,
- process data,
- error sequence and reason.

The information listed above is essential for making justified and optimal decisions that ensure more efficient: production planning, use of resources, maintenance of equipment, and planning of it. The working principle of the Dimusa monitoring system is presented in Figure 1.

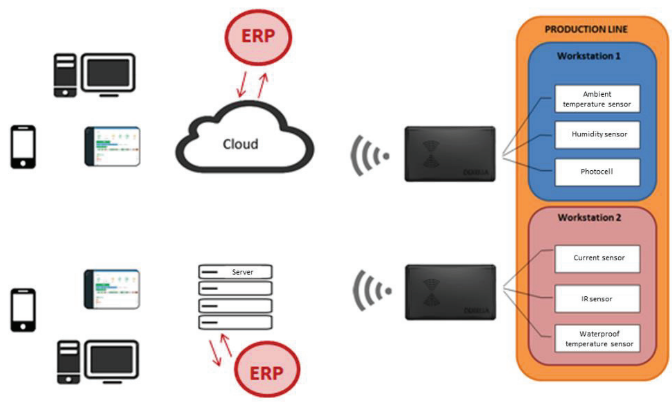

Figure 1 The principal scheme of Dimusa system

The Dimusa real-time production monitoring and prediction system integrate the following core modules:

- Data collection (process and production).
- Analysis of collected data.

- Process and product-dependent visualization.
- Database.
- Data security and confidentiality.

The sensor system collects various data from the workstations (ambient temperature, pressure, duration, offsets, and electroluminescence). There are different types of sensors that can be connected to the input terminals of the Dimusa control unit.

Dimusa system application in a company

The sensors (Figure 3) were installed on CNC bending machine (Amada HFBO 50-20), which is described as a productive unit, and on the industrial robot (Motoman MRC SK-16), which is described as an operative unit in a robot-based workplace. The quality of monitored data, for example, the occurrence of errors and machine stops are reported by the responsible operator who observes the robot-based work cell. If the reason is unknown, it is complicated to offer a result with the decision algorithm

Overall, the system measures 5 KPI parameters [12], Figure 2:

- Overall Equipment Effectiveness (OEE) which is a standard form of measuring manufacturing productivity.
- Availability which considers unplanned and planned stops,
- Performance which considers slow cycles and small stops,
- Quality which considers defects,
- Speed which indicates time per one piece.

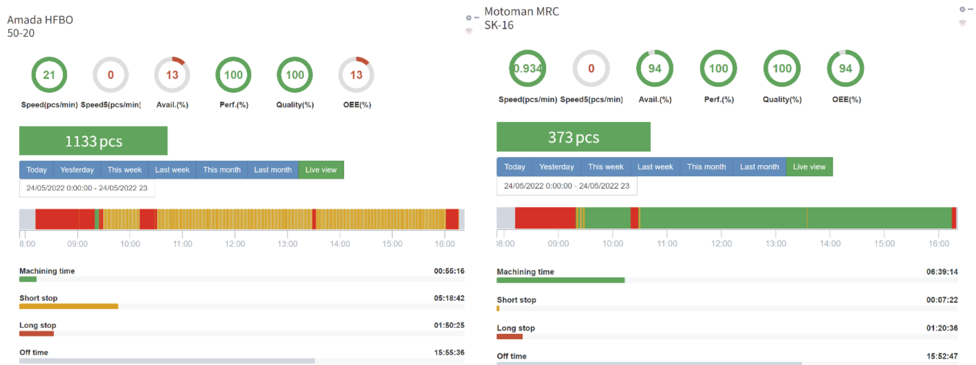

Figure 2 Dimusa monitoring panel

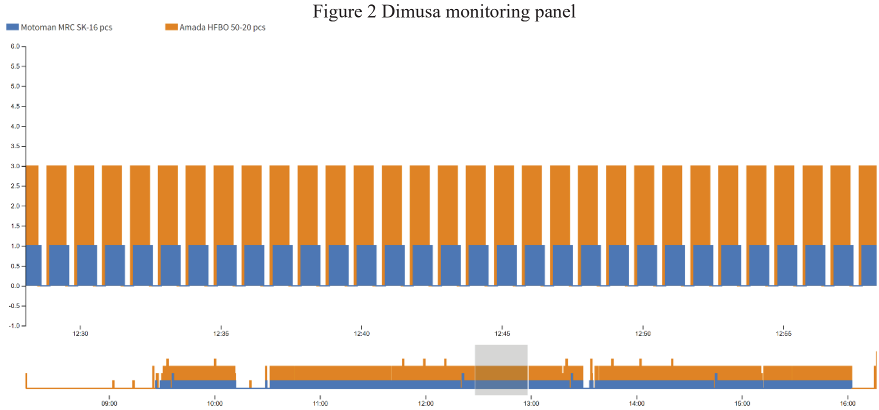

Figure 3 Example of Amada CNC bending machine sensor activities

SHOP FLOOR SIMULATION USING COLLECTED DATA

The production and process data, which is measured and collected in previous paragraph, is momentous information input for running simulations with different scenarios. For the company, a virtual robot-based workplace model was created, using Visual Components software. It is a tailor-made digital environment and describes the physical manufacturing unit identically Figure 5.

In the virtual model, it is essential to present the behaviour of a real production system in a realistic and equally dynamic way by using physical cell data and appropriate KPIs. One of the greatest advantages of simulation is to animate a system behaviour with time. As manufacturing simulation, a way to analyse and experiment production processes in a virtual setting which leads to reduce the time and cost requirements associated with physical testing. Moreover, it assesses inventory, assembly, transportation, and production within a simulation model, resulting information helps to improve target KPIs.

The bending cell AS-IS activities were observed in the real environment, layout was mapped, resources and buffers were identified that are executing the whole bending process of sheet metal. Based on that information a process flow was constructed (Figure 5), where each activity and corresponding resource are marked. The process starts with the picking of a blank sheet metal by a robotic arm, positioning of the blank at positioning table, followed by loading of blank in the bending machine, then bending activity, unloading of bended part, and placing the bended part in the pallet by industrial robot as a finished good. Subsequently, the process flow helps to create the 3D simulation model, where the analysis was conducted, and knowledge was captured for the improvement in the throughput of the bending cell.

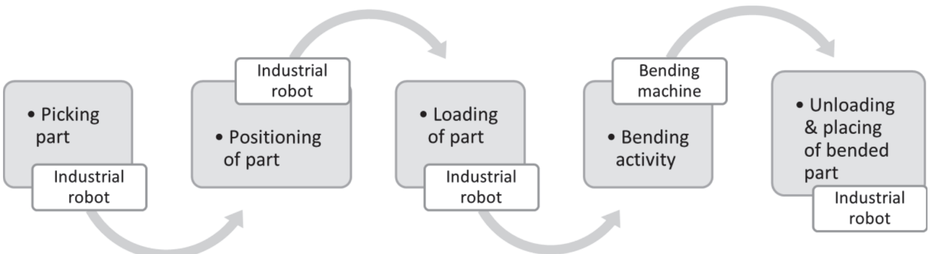

Figure 4 Process flow of robot bending cell

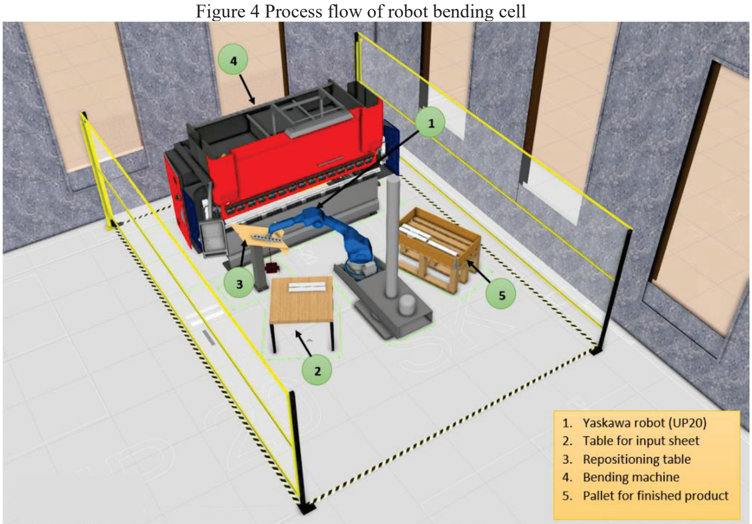

Figure 5 Virtual simulation model of bending cell in 3D environment

CONCLUSION

In this study, the importance of Cloud-based Services and Data Analytics have been discussed. Connecting the manufacturing to Industrial Internet gives the ability to the next generation digital tools to support, monitor, and predict production results in the future. Data exchange through Cloud-based services, such as REST API allows transferring data to different platforms, using several formats to execute it. There are benefits to gain from these tools: tools are inexpensive with no necessity of physical hardware, the resources or data can be acquired in a short time, mobility – user requires only internet access, collaboration – access is enabled securely worldwide.

In the practical Use case, we concentrated on an SME's robot-based sheet metal production unit, where the robot fulfills the operative unit, and the bending machine fulfills the production unit. Data collection and integration were carried out using the Dimusa system, a model-based, real-time production monitoring, and prediction system with optimal functionality. Sensors were applied to industrial robot and CNC bending press. According to selected KPIs, we measured: OEE, availability, performance, quality, and speed. The measured process data was input for creating a simulation model to evaluate the layout of the robot-based workplace. Moreover, in the future, we can carry out simulations to optimize the working cycle of a robot-based workplace. Also, to build an automatic dataflow between the real production workplace and virtual model, creating a functional digital twin, where data exchange will work both ways.

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REFERENCES

1. D. Davis; Industrial Transformation, The IX Network, a division of IQPC, (2022), available at https://www.industrialtransformationnetwork.com/personal-process-safety/articles/addressing-europes-manufacturing-worker-shortage
2. M. Behun, B. Gavurova, A. Tkacova, A. Kotaskova, *The Impact of the Manufacturing Industry on the Economic Cycle of European Union Countries* (Journal of Competitivness Vol 10, Issue 1, 2018) pp. 23-29.
3. M.Moor, K. Vaher, J. Riives, T. Kangru, T. Otto, *Modern Robot Integrated Manufacturing Cell According to the Needs of Industry 4.0* (Proceedings of the Estonian Academy of Sciences, Tallinn, 2021) pp. 407-412.
4. J. Collin and A. Saarelainen*, Teollinen internet* (Talemtum, Helsinki, 2016), pp. 18-20.
5. Mahmood, K.; Karaulova, T.; Otto, T.; Shevtshenko, E. (2019*). Development of cyber-physical production systems based on modelling technologies*. Proceedings of the Estonian Academy of Sciences, 68 (4), 348−355.
6. Microsoft, What is cloud computing, (webpage, referred on 28.11.2022), Available at: https://azure.microsoft.com/en-us/overview/what-is-cloud-computing/
7. A. Kuzmiakova, *Computer Science and Web Technologies* (Arcler Press, Burlington, 2020), pp. 188-189.
8. R. Fielding, "*Architectural Styles and the Design of Network-based Software Architectures*," Ph.D. thesis, University of California, 2000.
9. R. Raja and D. Ludovic, *Building RESTful Web Services with Spring 5: Leverage the Power of Spring 5.0, Java SE 9, and Spring Boot 2.0* (Packt Publishing, Birmingham, 2018), pp. 7-8.
10. J. P. Michel, *Web Service APIs and Libraries* (ALA Editions, Chicago, 2013). pp. xl.
11. Seobility, REST API, (Webpage, Referred on 5.12.2022), Available at: https://www.seobility.net/en/wiki/REST_API
12. Vorne Industries Inc., Overall Equipment Effectiveness. What is OEE? (webpage, referred on 6.06.2022), Available at: https://www.oee.com/

Appendix 6

Publication VI

Raamets, Tõnis; Majak, Jüri; Karjust, Kristo; Mahmood, Kashif; Hermaste, Aigar (2024). Development of Process Optimization Model for Autonomous Mobile Robot Used in Production Logistics. Modern Materials And Manufacturing 2023: Tallinn, Estonia, 2-4 May 2023. Ed. Karjust, Kristo; Kübarsepp, Jakob. New York: AIP Publishing, #020008. (AIP Conference Proceedings; 2989). DOI: 10.1063/5.0189299.

Development of Process Optimization Model for Autonomous Mobile Robot Used in Production Logistics

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Abstract. Today's manufacturing companies have begun to increasingly use digital tools to increase their company production efficiency, to ensure a low-price level, high quality, and fast delivery time of the product or service in the conditions of increasing competition in the globalized economy. An important part of improving the company's efficiency indicators is the ever-more relevant organization of transport operations on the production floor and the digitization and automation of these processes. More and more companies have adopted or plan to do so in the near future with autonomous mobile robots (AMR) to manage production logistics. The rapid development of the Internet of Things (IoT) and the advanced hardware and control software of AMR enable autonomous operations in dynamic environments, which gives them the ability to communicate and negotiate independently with other resources, such as machines and systems, and thus decentralize decision-making in production processes. Decentralized decision-making allows the system to dynamically respond to changes in system state and environment. Such developments have affected traditional planning and control methods and decision-making processes, but also place greater demands on the software used and integrated Artificial Intelligence (AI) algorithms for the execution of these decisions. In this study, we provide an overview of how to pilot the integration of an AMR system with AI functionality in the production logistics of the food industry using the concept of a 3D virtual factory. The paper proposes an approach for the performance analysis of AMR for the transportation of goods on the production factory floor, which is based on 3D layout creation and simulation, monitoring of key performance indicators (KPIs), and integration of AI for proactive decision-making in production planning. The relevance and feasibility of the proposed approach are demonstrated by a food industry case study.

INTRODUCTION

Autonomous mobile robots (AMR) have been introduced in various fields of modern industry to increase efficiency, productivity, and safe transport of goods, which perform various predetermined transport tasks without direct operator intervention [1]. Usually, the manufacturers of such AMR systems also have control software that enables various transport missions to be performed both in automatic mode and via a human-machine interface (HMI) according to predetermined routes [2].

With the continuous increase in the use of AMR systems, various problems such as deadlocks and conflicts arise, which cause a decrease in the efficiency of these systems [3]. Also, the complexity of managing and controlling these AMR systems is an important factor, which limits their implementation in a small or medium-sized company and inhibits their effectiveness in fulfilling transport tasks.

To analyze the feasibility and efficiency of such AMR systems, a conceptual model based on 3D visualization, simulation, the use of IoT sensors and experimental research should be used in advance [4] to monitor the existing KPI's in the real work condition [5,6]. Such an approach provides a comprehensive overview of the concept and performance indicators (KPIs) of a possible AMR solution before its implementation in the company's production logistics. Moreover, the automation of production processes through robotization can address the Lean wastes effectively [7] and hence, productivity can be improved by implementation of Lean tools [8] that are affirming the implementation of AMR on the factory floor.

Recently, an intelligent AI based algorithms like ant colony optimization [9], genetic algorithm [10], A* algorithm [11], simulated annealing [12], etc. are recognized as powerful tools for mobile robot path planning. In the current study the combinatoric and AI based algorithms are considered based on workgroup long time experience with AI tools and methods in wide range of engineering applications [13,14]. The conceptual model of production logistics also gives us a better understanding of how to organize the optimal and effective management of AMR systems and how to integrate it with the company's IT systems.

In this article, the authors focus on the creation of configurable automated logistics solutions, including the use of artificial intelligence functionalities and 3D simulation software for the virtualization and simulation of production logistics. Based on artificial intelligence-based tools, various algorithms are proposed for easy reconfiguration and planning of tasks and movement paths of mobile robots.

PROPOSED APPROACH FOR AMR PERFORMANCE ANALYSIS

The proposed approach to analyze the performance and the implementation of AMR for the transportation of goods on the factory floor is adopted from our previous study [15] as shown in Figure 1, where we include AI elements for proactive decision-making along with the simulation analysis. The developed approach can be used to automate the process of production logistics with the help of immersive 3D simulation analysis as a validation of the concept. Its implementation can be verified through experimental testing in a real factory environment.

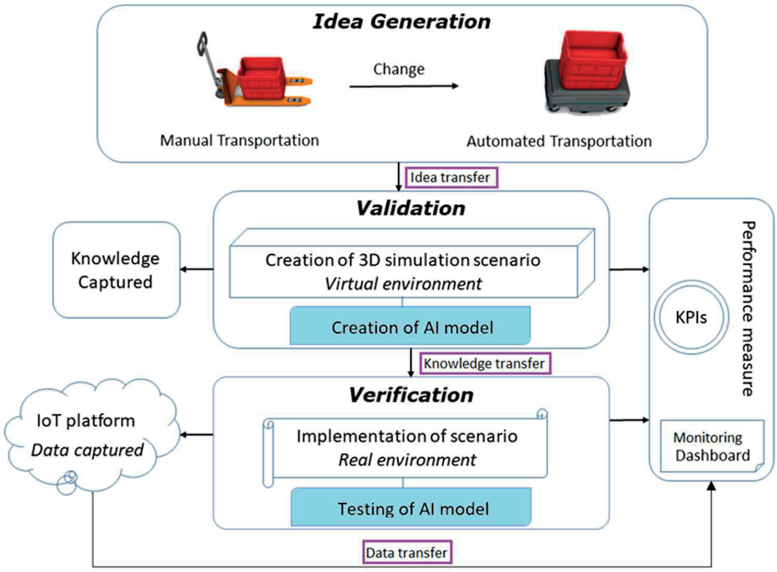

Figure 1. Proposed approach to analyze the performance of AMR for production logistics [15]

The proposed approach has three main stages that begin with the idea generation to automate a process through a brainstorming activity. From an outcome of brainstorming, the second stage is to develop a virtual model of the process of production logistics, simulate and analyze that process through KPIs in the 3D virtual environment, and the knowledge as an outcome of the second stage can be used to implement AMR in the real environment. The simulation model also helps to create an AI model, which can be validated by different simulation scenario analysis. The third stage is the implementation and testing of simulation model of a mobile robot along with the AI model as an experimental use-case, where the data can be captured through IoT sensors, calculations should be made for KPIs and visualize the performance of the mobile robot by a monitoring dashboard. In this study, the focus is to create a layout and simulation of the AMR transportation process in a 3D environment and conduct the performance analysis. Moreover, an AI model was also developed for the route planning and optimal path-finding of AMR. The case study is used as a research method to attain the feasibility of the proposed approach.

Virtual model and simulation of food industry use-case

The virtual model for setting up the layout and simulation of AMR routings was created on the Visual Components software [16]. Movement and path planning of AMR is defined as follows: Ten plastic red boxes were transported (carrying) by AMR at every run on the red paths as shown in Figure 2. and the consolidated view of routings, buffers for picking and placing goods (boxes) by AMR is depicted in Figure 3.

Setup for plastic boxes:

- **Path 1-2 & 1-3:** Transportation of washed empty boxes by AMR (picking plastic red boxes from buffer 1, placing at buffer 2 and buffer 3
- **Path 2-4:** Transportation of filled boxes by AMR (picking plastic red boxes from buffer 2 and placing at buffer 4)
- **Path 4-5:** Transportation of dirty empty boxes by AMR (picking plastic red boxes from buffer 4 and placing at buffer 5)

Figure 2. AMR pathways setup on factory layout (setup a: for red boxes)

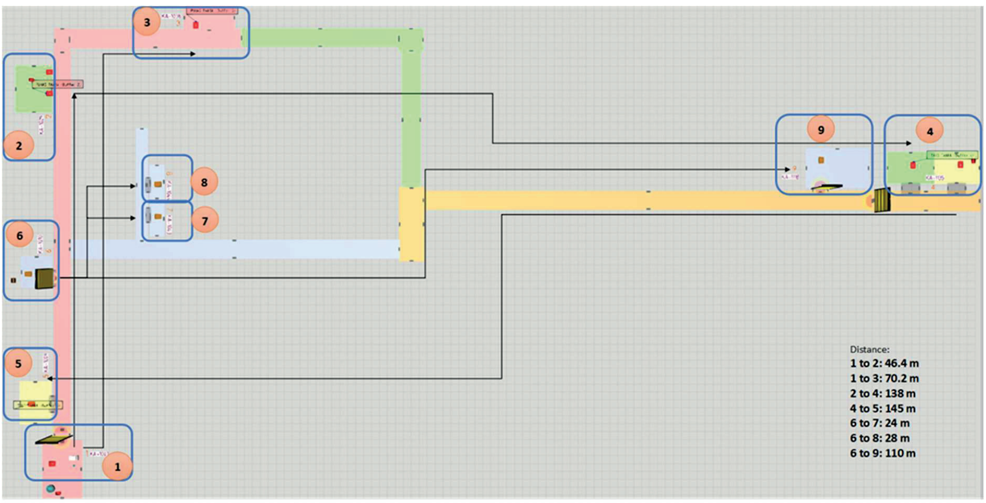

Figure 3. AMR routing map, buffers for picking and placing of boxes

KPIs and simulation analysis of AMR

The number of boxes transported, *time of transportation*, and *average utilization* of AMR were selected as KPIs for the analysis and optimization of AMR movement. Two scenarios were tested, the first scenario with an AMR speed of 1 m/sec and the second one with an AMR speed of 0.5 m/sec. The result of the simulation analysis is described in Table 1.

Table 1. AMR simulation analysis

Performance parameter	Scenario 1: AMR Speed 1 m/sec	Scenario 2: AMR Speed 0.5 m/sec
Plastic red boxes		
Number of boxes transported	Buffer 2 and 3: 400 pcs, Buffer 4: 400 pcs, Buffer 5: 400 pcs	Buffer 2 and 3: 400 pcs, Buffer 4: 400 pcs, Buffer 5: 400 pcs
Total time of transportation	369 minutes (6 hours & 9 minutes)	594 minutes (9 hours & 54 minutes)
AMR average utilization	100 % (continues movement of AMR)	100 % (continues movement of AMR)
AMR pick & place time	60 sec	60 sec
Total travel distance by AMR	14.5 km	14.5 km

USING THE FUNCTIONALITY OF ARTIFICIAL INTELLIGENCE IN THE PATH PLANNING OF MOBILE ROBOT'S

This task focuses on the development of AI-based decision-making systems for mobile robots, depending on the task execution and production schedule. This includes the identification of decision criteria, key influencing factors, and prioritization. The task under consideration is closely related to the task of optimizing work paths for mobile robots. Decision-making in the considered digitalized solution is based on gathering maximum online information and analyzing it. Therefore, the main influencing factors are the information obtained from the sensor system and ERP (Figure 4).

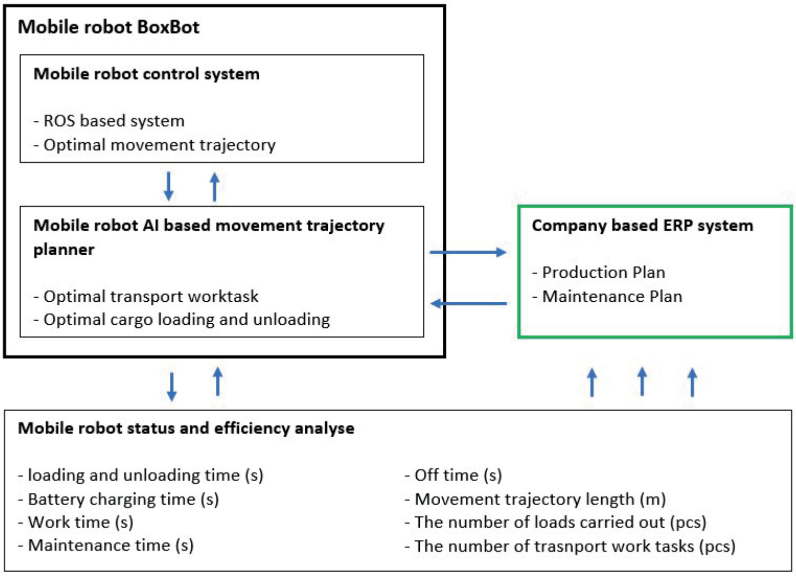

Figure 4. Principle diagram of AMR data exchange

Simplified description of the node

Particularly, to plan the movements of a mobile robot, it is necessary to receive real time information from the sensor system at each node. The nodes are divided into a starting node, an array of input nodes (all points where goods can be picked up), output node(s) where the goods need to be taken, and auxiliary nodes (washing, maintenance, loading), etc. The information is needed in each node depends to some extent on the specific task.

A visualized example of one production node is given in Figure 5. The object-oriented programming approach is utilized. The node class includes the following necessary information:

- the number of the node (in essence, it also determines the location),
- the availability of the goods for pickup (Loading),
- the availability of a place to drop off the empty tare (Unloading),
- time (allows to determine the remaining allowed waiting time).

At the moment, each node has Loading and Unloading values of 0 or 1. The time attribute characterizes the remaining time until preservation (allowed transport time in this case), if it is below the given critical value, then the priority of moving the given goods is higher.

The above simplified description of the node can be utilized for all subtypes of nodes. Each particular node is introduced as instance/object of the node class. Two node arrays are composed for input and output nodes, respectively.The node data is an important part of the necessary information for making decisions, but in addition to this, there is also more general information for creating a directed graph characterizing the entire movement. This requires a 2D array/table of all nodes, specifying from which node to which node it is possible to move, as well as the distances between nodes, etc. If the application already has some user experience and has collected enough data on travel times, then it seems reasonable to replace path lengths with travel times.

Selection of shortest path algorithms

The shortest path algorithm is used to determine optimal mobile robot path. Herein the shop-floor application for food industry is considered as a case study (Figure 6). main decision criteria for the robot's movements are the need and ability to move the goods or the tare (is there something to pick up and is there somewhere to put it down), the allowed time limit (if the deadline for moving some goods to the output node is below a predetermined value, i.e. the shelf life limit is approaching) and the shortest path.

At each location/node Figure 5, two “simple” decisions are required:

a) where to move (to which node), you have to decide based on information from online sensors, etc

b) how to move can be planned by generating the shortest paths between nodes in advance

A robot's motion path can be represented as a directed graph since movement between some nodes is only allowed in one or both directions.

Among shortest-path algorithms, the genetic algorithms (GA), the ant colony algorithms (ACO), and the combinatorics algorithms have been considered. The Dijkstra algorithm, which has a time complexity of O(E+log(N)*N), has been chosen from the two observed combinatorics algorithms. Here N is the number of vertices (nodes) of the graph and E is the number of edges. The "Dijkstra" algorithm is faster than another widely used Bellmann-Ford combinatorics algorithm with a time complexity of O(N*E). The work done by Dijkstra's algorithm can be made faster by applying artificial neural networks. The time complexity of the evolutionary algorithms like GA and ACO depend on particular operators used/designed. In the case of considered simple case study the evolutionary algorithms appear slower. The advantage of evolutionary algorithms is capability to solve complex problems.

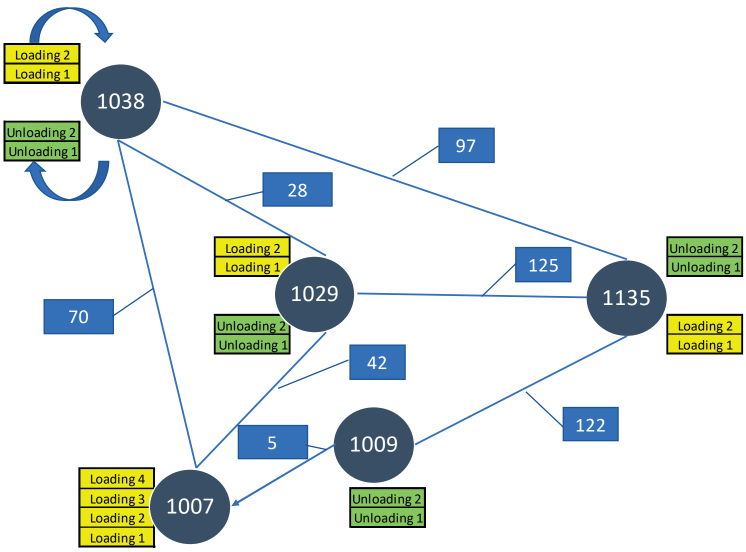

Figure 5. AMR motion model for the food industry use case

The optimal path for AMR motion model shown in Figure 6 (1007 is start node, 1029 and 1038 are input nodes, 1135 is output mode, 1009 is wash node) is depicted in Figure 6 as red line in directed graph (Figure 6). The optimal path of one “mission” of the mobile robot consists of three subpaths from start node to selected input node, next to selected output node and finally back to start node (all based on online information). The length of the optimal path 1007-1038-1135-1009-1007 is 294 units. Obviously, the optimal bath depends on distances (as weights) and sensor data specifying availability for Loading/Unloading, also time determining priorities of the nodes.

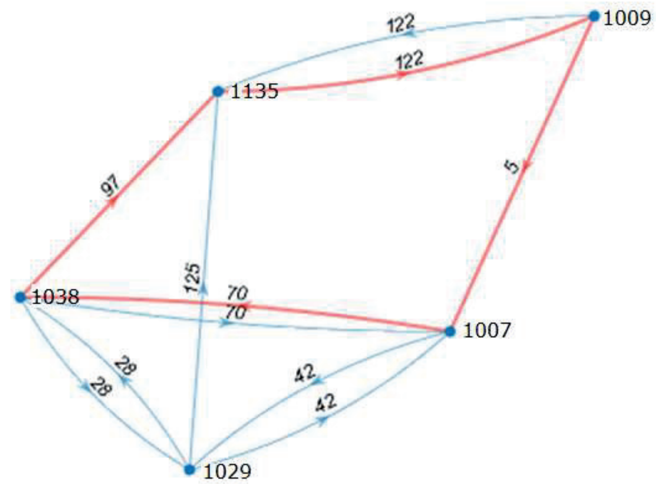

Figure 6. Optimal path for AMR motion

CONCLUSION

The main goal of this study was to analyze whether and how autonomous mobile robots can be used in the food industry based on use case, and whether they can be interfaced with the control system of mobile robots with artificial intelligence (AI) functionality and with the company's existing resource planning system in order to optimize the movement trajectories and transport tasks of mobile robots through their interaction.
During the research, the VF concept was created, where a 3D virtual factory of the food industry, created on a 2D floor plan of a physical factory, was used to analyze the feasibility of using a mobile robot. Real production data was used as input for the VF simulation. This approach is a quick and less time-consuming process for solving a specific problem of a manufacturing company, and the results obtained are concrete and easy to interpret.
The concept was proposed to create a cyber-physical environment, where an enterprise resource planning system (ERP), a mobile robot control system, a virtual factory with workplaces and artificial intelligence functionality to solve robot planning tasks are interfaced. This approach allows us to test the suitability of various solutions in advance on the basis of a virtual factory and to find which solution is the most optimal for the use of artificial intelligence and the most cost-effective for the company.
Based on the principle of a decentralized control system, building control models using artificial intelligence for AMR transport missions is much more efficient than using it in conjunction with the VF concept. With such a novel approach, AMR systems can be simulated in advance, optimized and made more efficient in order to ensure a much easier and faster generation of the transport tasks assigned to them, and thereby achieve efficient and flexible movement of goods on the factory floor and integration with other production systems.

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REFERENCES

1. Fragapane, G.; Koster, R.; Sgarbossa, F.; Strandhagen, J. (2021). Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda. European Journal of Operational Research Volume 294, Issue 2, 16 October 2021, Pages 405-426. https://doi.org/10.1016/j.ejor.2021.01.019.
2. De Paula Ferreira, W., Armellini, F., De Santa-Eulalia, L.A. (2020). Simulation in industry 4.0: A state-of-the-art review. Computers and Industrial Engineering, Vol. 149, p. 106868.
3. De Ryck M, Versteyhe M, Debrouwere F. (2020) Automated guided vehicle systems, stateof-the-art control algorithms and techniques. Int J Ind Manuf Syst Eng 2020;54:152–73. https://doi.org/10.1016/j.jmsy.2019.12.002.
4. Raamets, T.; Karjust, K.; Hermaste, A.; Mahmood, K. (2021). Planning and Acquisition of Real-Time Production Data Through the Virtual Factory in Chemical Industry. Proceedings of the ASME 2021, 2B: Advanced Manufacturing: International Mechanical Engineering Congress and Exposition IMECE2021, November 1–5, 2021 Virtual (Online), USA.. ASME Digital Collection , V02BT02A017. DOI: 10.1115/IMECE2021-73080.
5. Musthafa, Muhamad Danial Amzar;Thamrin, Norashikin M.(2020), „An IoT-based production monitoring system for assembly line in manufacture“, International Journal of Integrated Engineering, Vol. 12, Issue 2, Pg 38 – 45.
6. Bonci A., Di Biase A., Giannini M.C., Indri M., Monteriu A., Prist M. (2022) An OSGi-based production process monitoring system for SMEs, IECON Proceedings (Industrial Electronics Conference)Volume 2022-October 2022 48th Annual Conference of the IEEE Industrial Electronics Society, IECON 2022.
7. Karaulova, T.; Andronnikov, K.; Mahmood K.; Shevtshenko, E. (2019). Lean Automation for Low-Volume Manufacturing Environment, Proceedings of the 30th DAAAM International Symposium, pp.0059-0068, B. Katalinic (Ed.), Published by DAAAM International. DOI: 10.2507/30th.daaam.proceedings.008.
8. Mahmood, K. Shevtshenko, E. (2015). Productivity Improvement by Implementing Lean Production Approach. Proceedings of the 10th International Conference of DAAAM Baltic "Industrial engineering", 12-13 May Tallinn, Estonia, DAAAM International Vienna, DAAAM Baltic. (1−7).
9. Wu, L; Huang, X.; Cui, J.; Liu, C.; Wensheng Xiao, W. (2023) Modified adaptive ant colony optimization algorithm and its application for solving path planning of mobile robot. Expert Systems with Applications 215, 119410. https://doi.org/10.1016/j.eswa.2022.119410.
10. Chen, Y. Q., Guo, J. L., Yang, H. D., Wang, Z. Q., & Liu, H. L. (2021). Research onnavigation of bidirectional A* algorithm based on ant colony algorithm. The Journal of Supercomputing, 77, 1958–1975. https://doi.org/10.1007/s11227-020-03303-0.
11. Chong, Y., Chai, H. Z., Li, Y. H., Yao, J., Xiao, G. R., & Guo, Y. F. (2021). Automatic recognition of geomagnetic suitability areas for path planning of autonomous underwater vehicle. Marine Geodesy, 44, 1–15. https://doi.org/10.1080/.
12. Takwa, T., & Saoussen, K. (2021). A Simulated annealing-based recommender system for solving the tourist trip design problem. Expert Systems with Applications, 186, Article 115723. https://doi.org/10.1016/j.eswa.2021.115723.
13. Pikner, H.; Sell, R.; Majak, J.; Karjust, K. (2022), Safety System Assessment Case Study of Automated Vehicle Shuttle, Electronics, 11 (7), 1−16. DOI: 10.3390/electronics11071162.
14. Paavel, M.; Karjust, K.; Majak, J. (2017). Development of a product lifecycle management model based on the fuzzy analytic hierarchy process, Proceedings of the Estonian Academy of Sciences, 66 (3), 279−286. DOI: 10.3176/proc.2017.3.05.
15. Mahmood, K.; Karjust, K.; Raamets, T. (2021). Production Intralogistics Automation Based on 3D Simulation Analysis. Journal of Machine Engineering, 21(2),102−115. DOI: https://doi.org/10.36897/jme/137081.
16. VISUAL COMPONENTS PREMIUM 4.4 https://www.visualcomponents.com/, (accessed 15, November 2022).

Appendix 7

Publication VII

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Virtual factory model development for AI-driven optimization in manufacturing

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AI IN MANUFACTURING

RESEARCH ARTICLE

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ABSTRACT

This paper examines the development of a virtual factory model to optimize overall equipment effectiveness (OEE) in a planned manufacturing facility. Using digital simulations based on a wood manufacturing setup, AI-driven models can be applied to analyze specific OEE metrics, allowing for targeted identification of production bottlenecks and efficiency improvements. The virtual factory enabled scenario testing for the proposed facility, providing actionable insights without impacting current operations. The preliminary results indicate that AI integration within a virtual factory can significantly enhance planning and decision-making for future production investments.

Introduction

Enhancing competitiveness and efficiency in manufacturing processes is a key priority in modern industry [1]. The optimization of production workflows through advanced technologies such as artificial intelligence (AI) and virtual factories offers innovative solutions for addressing bottlenecks and improving overall operational performance [2]. This study focuses on analyzing and optimizing the production processes of a wood manufacturing company by employing a virtual factory model augmented with AI-based tools [3]. In this study, the virtual factory evaluates a new manufacturing facility layout and production flows at the early design stage. Unlike previous studies that broadly explore AI applications in manufacturing [4], this research explicitly applies AI-driven clustering for real-time overall equipment effectiveness (OEE) optimization in wood manufacturing. The novelty of this approach lies in proactively integrating AI clustering techniques to detect and mitigate bottlenecks in a virtual factory environment. This allows manufacturers to simulate and refine production strategies before implementation, ensuring data-driven improvements in efficiency and cost reduction. The research investigates the production process of wooden window frames and doors, encompassing computer numerical control (CNC)-based machining and assembly tasks, material impregnation, and painting workflows. The primary challenges include balancing production flows, optimizing equipment utilization, and enhancing quality control. Using the Siemens Tecnomatix Plant Simulation (STPS) platform, the production flows of the new facility were modeled, and the optimal allocation of workstations and production resources was assessed [5]. The findings demonstrate that the virtual factory model, combined with the AI-driven analysis, is an effective tool for optimizing manufacturing processes.

Proposed approach for production process optimization and analysis

Optimizing production processes in wood manufacturing has become a critical requirement for ensuring competitiveness, operational efficiency, and adaptability to evolving demands. In the wood manufacturing industry, unique challenges arise due to the complexity of workflows, resource dependencies, and variability in product specifications. Addressing these challenges requires a systematic approach that combines cutting-edge tools and data-driven strategies. This study proposes a multifaceted methodology to tackle inefficiencies and enhance productivity within the wood manufacturing company's operations. The proposed approach consists of three key components: (1) virtual factory modeling, (2) real-time data collection, and (3) AI-based analysis. STPS was used to create a digital twin of a wood manufacturing facility, including CNC machining, material handling, and finishing workflows. The model was built using real-world production data provided by the company. We applied k-means clustering ($k = 5$, determined using the elbow method) to OEE data collected over three months to analyze production inefficiencies. The clustering algorithm segmented inefficiencies into meaningful categories, identifying underperforming workstations and recurring bottlenecks. The cluster validity was assessed based on the stability of identified workstation groups and their correlation with real production inefficiencies observed in the factory. As part of the AI-driven analysis, we identified the five worst-performing (bottleneck) workstations and the five best-performing workstations based on the OEE metrics. These insights were visualized to highlight key areas for process optimization and efficiency improvements. The identified bottleneck workstations exhibited higher idle times and lower throughput, whereas the best-performing workstations demonstrated stable efficiency with minimal downtime. The proposed framework builds upon prior research into the integration of virtual factory environments with autonomous systems for production logistics optimization [6]. Unlike previous approaches, this study focuses specifically on AI-assisted decision-making within a virtual factory environment in the wood manufacturing sector. The combination of real-time monitoring and AI-driven clustering analysis enables manufacturers to pre-emptively adjust workflows, enhancing production efficiency and flexibility.

Figure 1 illustrates a systematic approach to optimizing production processes in the wood manufacturing industry. It highlights three key components: virtual factory, which enables the simulation and analysis of workflows; real-time data collection, which gathers operational data from the manufacturing floor; and AI-based analysis, which processes data to identify bottlenecks, predict inefficiencies, and provide actionable insights. Inputs such as machine specifications, workflow details, and production goals feed into the system, while outputs include optimized workflows, balanced resources, and improved quality control. These elements create a scalable and cost-efficient framework for addressing inefficiencies and enhancing productivity.

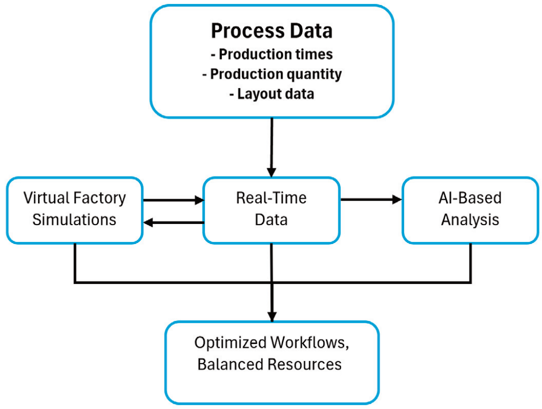

Fig. 1. Proposed framework for production process optimization.

Integration of the virtual factory environments (case study)

Virtual factories, developed like digital twins, are digital representations of physical manufacturing systems that enable detailed modeling, simulation, and optimization of production processes without disrupting real-world operations. These environments allow manufacturers to analyze workflows, machine interactions, material handling, and human resource allocation within the production line, facilitating informed decision-making and process improvements [7]. In this study, a comprehensive virtual factory model was developed for a wood manufacturing company. This tool enables the creation of a digital twin that replicates the physical production environment, allowing for a detailed analysis and testing of workflows without interfering with actual operations. The virtual factory model integrates essential production processes, including CNC machining, assembly, material handling, and finishing workflows. Key inputs, such as machine specifications, cycle times, and production targets, were provided by the company and integrated into the model to accurately replicate real-world conditions. Through this virtual representation, various production scenarios were simulated to predict potential inefficiencies, identify bottlenecks, and assess the impact of proposed changes on system performance. For instance, layout adjustments and transport flow optimization scenarios were tested to improve throughput and reduce idle time. Such applications of virtual factories enable manufacturers to experiment with process designs, resource allocations, and operational strategies without the risks and costs of physical trials. The effectiveness of virtual factories in manufacturing optimization has been extensively demonstrated in recent studies. Digital twin systems have been shown to enhance production efficiency by enabling real-time monitoring and predictive analytics, leading to significant reductions in downtime and improved resource utilization [8]. Additionally, virtual factory models have proven effective in streamlining workflows and optimizing resource allocation, resulting in lower operational costs and higher throughput [9].

Figure 2 presents the virtual factory model created for the wood manufacturing company using the STPS software. The layout depicts the production flow, encompassing CNC machining, assembly, material handling, and finishing workflows. Accompanying the model is a "Resource Statistics" chart, which provides insights into key performance indicators (KPI) such as resource utilization, working times, idle times, and bottlenecks across various stations. This virtual factory model facilitated the simulation of production scenarios, including layout optimization and transport flow improvements, identifying inefficiencies, and the development of actionable strategies to enhance overall throughput and reduce idle time.

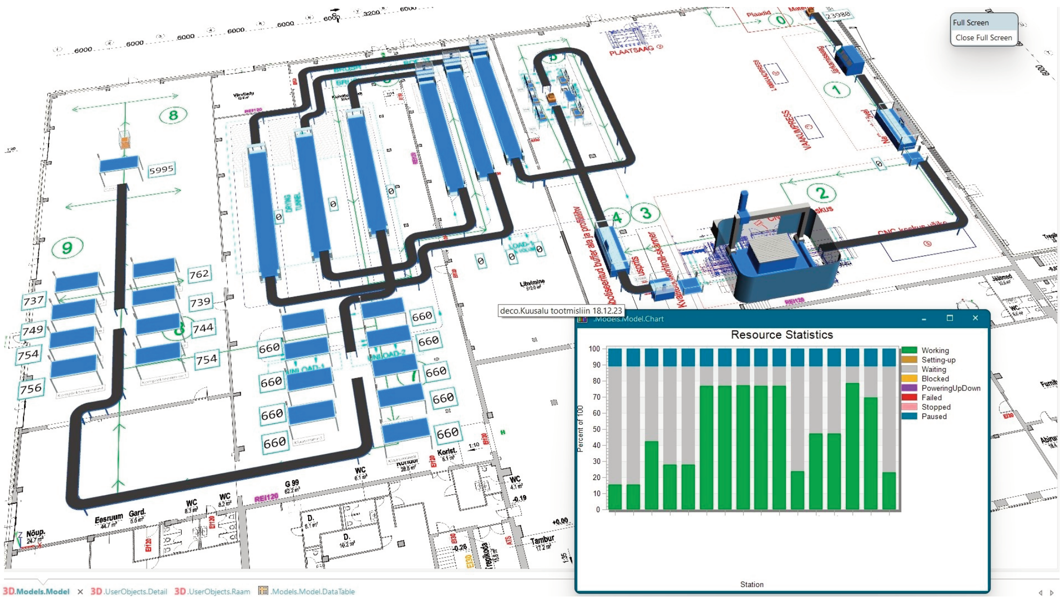

Fig. 2. Virtual factory model developed using STPS.

Real-time data collection for enhanced accuracy

Real-time data collection, enabled by manufacturing execution systems (MES), provides critical metrics such as machine availability, cycle times, resource utilization, and defect rates. These metrics are integrated into the virtual factory model to ensure that it remains an accurate and dynamic representation of the physical production environment. Continuous monitoring supports effective simulations and data-driven workflow optimization [10]. MES with real-time data collection capabilities ensure operational transparency, enabling real-time adjustments to workflows and enhancing production efficiency. Integration with digital twin technology has been shown to improve OEE through enhanced scheduling accuracy and predictive maintenance [11]. This capability is essential in dynamic manufacturing environments, where agility and responsiveness are critical for adapting to fluctuating production demands. The DIMUSA MES interface, as shown in Fig. 3, visualizes critical production metrics for specific machines, such as a crosscut saw and a four-sided planer. These dashboards display KPIs [12,13], including availability, performance, quality, and OEE. The system tracks real-time working hours, short stops, long stops, and off times, providing a clear overview of machine performance and utilization.

This visualization enables factory operators to monitor production in real-time, identify inefficiencies, and make immediate adjustments to workflows. By integrating this data into the virtual factory model, decision-makers can enhance process accuracy and efficiency. Real-time data collection aligns with Industry 4.0 principles, facilitating automation, connectivity, and the use of advanced analytics. These systems enable factories to transition seamlessly between production scenarios, reducing downtime and improving resource allocation.

AI-based analysis for data-driven optimization

AI plays a pivotal role in the proposed methodology by analyzing the collected data and generating actionable insights. By leveraging AI-driven clustering techniques, production inefficiencies can be identified more effectively, allowing manufacturers to address systemic bottlenecks before they escalate into major disruptions. This study applied clustering methods to OEE metrics to identify patterns and segment production data into meaningful groups. K-means clustering ($k = 5$, determined using the elbow method) was selected as the primary approach due to its efficiency in handling large industrial datasets and its ability to create clearly defined clusters based on similarity measures. K-means clustering was chosen over other machine learning approaches, such as hierarchical clustering or Gaussian mixture models, due to its efficiency, scalability, and adaptability to manufacturing environments. The time complexities of the k-means clustering, hierarchical clustering and Gaussian mixture models are given in Table 1 [14].

It can be observed from Table 1 that in the case of large dataset capacity, the time complexity of the k-means clustering is substantially lower than that of hierarchical clustering. The Gaussian mixture models complexity is higher due to covariance computations. Unlike deep learning methods, k-means provides interpretable cluster assignments, enabling engineers to quickly identify underperforming machines or processes. Since OEE metrics fluctuate based on production schedules, k-means effectively groups machines by performance trends, making it easier to track changes over time and

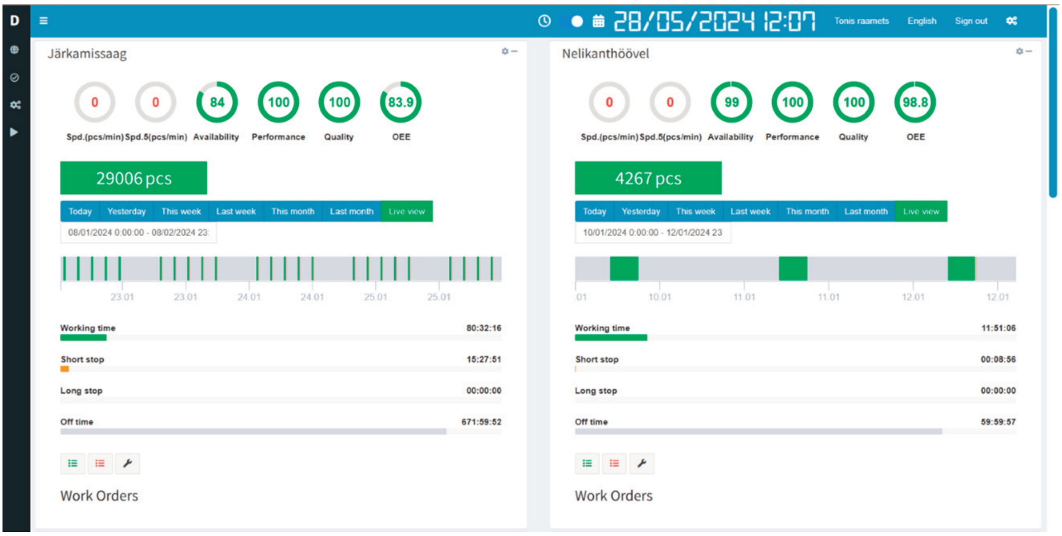

Fig. 3. DIMUSA system interface for real-time data collection.

Table 1. Comparison of time complexities

Time complexity	K-means clustering	Hierarchical clustering	Gaussian mixture models
	$O(n * k * d)$	$O(n^2 \log(n))$ – optimized	$O(n * K * d)$
Meaning of parameters	n – number of data points, k – number of clusters, d – number of dimensions	n – number of data points	n – number of data points, k – number of Gaussian components, d – number of dimensions

implement data-driven optimizations. The proposed approach enables a deeper understanding of the factors affecting availability, performance, and quality within the manufacturing process. By applying clustering algorithms to OEE metrics, specific production bottlenecks and inefficiencies were identified. These insights were used to optimize resource allocation, balance workflows across the production line, and implement targeted predictive maintenance strategies, reducing downtime and improving overall system performance. The clustering-based analysis has proven effective in manufacturing, offering precise optimization strategies that enhance production efficiency and resource utilization [15]. By incorporating these methods, this approach ensures a proactive and data-driven framework for optimizing manufacturing operations.

Figure 4 presents the results of the clustering analysis applied to the OEE metrics, visualized as a scatter plot. The x-axis represents availability (%), while the y-axis represents performance (%). Each point in the plot represents an individual workstation, and different colors indicate the cluster to which each workstation belongs based on its operational characteristics. The clustering analysis effectively groups workstations according to their efficiency levels, revealing patterns across the production environment. Workstations located in the lower-left quadrant exhibit both low availability and low performance, identifying them as critical bottlenecks that require intervention. In contrast, workstations in the upper-right quadrant maintain high availability and high performance, serving as benchmarks for optimal efficiency. This visualization provides a clear overview of production imbalances, helping manufacturers pinpoint underperforming workstations and analyze the causes of their underperformance. Workstations within the lowest-performing clusters often suffer from frequent downtime, suboptimal scheduling, or inefficient resource utilization. By leveraging these insights, targeted actions such as redistributing workloads, adjusting production schedules, or implementing predictive maintenance strategies can be taken to enhance efficiency. The ability to visually segment workstations based on OEE data ensures that production optimizations are data-driven rather than reactive. This approach allows for proactive decision-making, leading to more balanced workloads, minimized downtime, and improved overall production performance.

A scalable and cost-efficient framework

The key advantages of the proposed methodology are its scalability and cost efficiency. Unlike traditional trial-and-error approaches, which require significant time and resources, this integrated framework minimizes risks and provides immediate feedback on the feasibility of proposed changes. It is particularly well suited for dynamic manufacturing environments, where adaptability and responsiveness are crucial.

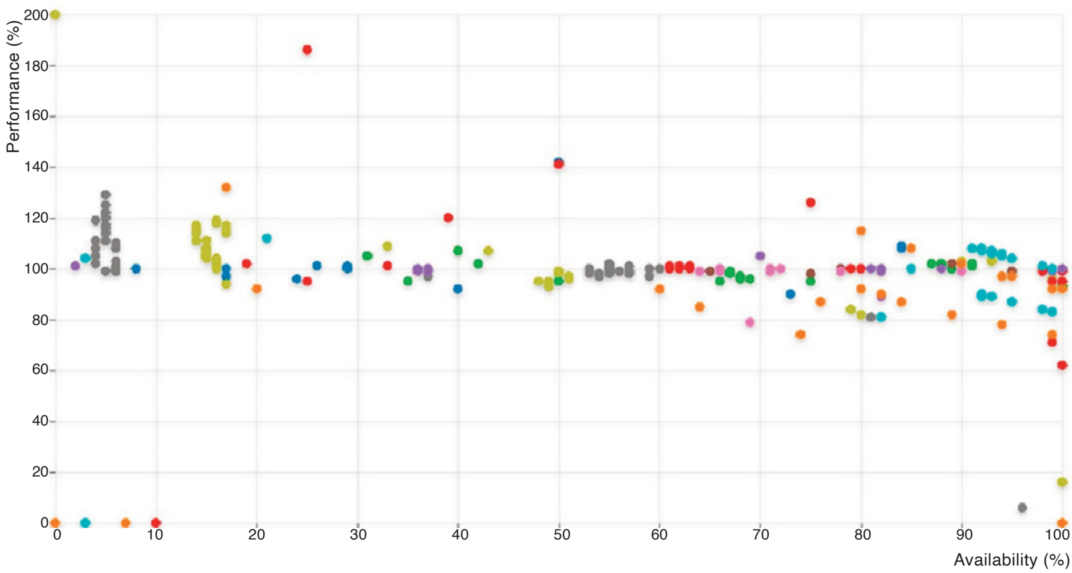

Fig. 4. Clustering analysis of OEE metrics (Dimusa MES).

By combining the predictive power of virtual factory models, the accuracy of real-time data collection, and the analytical depth of AI-based techniques, this methodology enables manufacturers to achieve continuous improvement and maintain a competitive edge in their industries.

Conclusion

The proposed approach presents a comprehensive framework for identifying inefficiencies and optimizing workflows in the wood manufacturing company. By combining advanced simulation tools, real-time monitoring systems, and AI-driven analysis, this methodology enables a deeper understanding of production processes and their performance. Simulation tools allow manufacturers to create a digital twin of the production environment, where different scenarios can be tested without disrupting actual operations. Real-time monitoring systems continuously collect production data, tracking machine availability, performance metrics, and potential bottlenecks. The AI-driven analysis processes this data, detecting patterns and inefficiencies that may not be immediately visible through traditional monitoring methods. By integrating these components, the proposed framework not only identifies operational weaknesses but also provides data-driven recommendations for improvements. This enables proactive decision-making, allowing managers to anticipate and address production challenges before they escalate. The result is a more efficient, resilient, and optimized manufacturing process, where resources are utilized effectively, workflows are balanced, and productivity is maximized.

Data availability statement

All data are available in the article.

Acknowledgments

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References

1. Zhang, Y., Du, H., Piao, T., Shi, H. and Tsai, S.-B. How manufacturing companies can improve their competitiveness: research on service transformation and product innovation based on computer vision. *J. Glob. Inf. Manag.*, 2024, **32**(1), 1–26. https://doi.org/10.4018/JGIM.336485
2. Wan, J., Li, X., Dai, H. N., Kusiak, A., Martinez-Garcia, M. and Li, D. Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. *Proc. IEEE*, 2021, **109**(4), 377–398. https://doi.org/10.1109/JPROC.2020.3034808
3. Debevec, M., Simic, M. and Herakovic, N. Virtual factory as an advanced approach for production process optimization. *Int. J. Simul. Model.*, 2014, **13**(1), 66–78. https://doi.org/10.2507/IJSIMM13(1)6.260
4. Subramaniyan, M., Skoogh, A., Bokrantz, J., Sheikh, M. A., Thürer, M. and Chang, Q. Artificial intelligence for throughput bottleneck analysis – state-of-the-art and future directions. *J. Manuf. Syst.*, 2021, **60**, 734–751. https://doi.org/10.1016/j.jmsy.2021.07.021
5. Siemens. Plant simulation software. https://plm.sw.siemens.com/en-US/tecnomatix/plant-simulation-software/ (accessed 2025-05-02).
6. Raamets, T., Majak, J., Karjust, K., Mahmood, K. and Hermaste, A. Autonomous mobile robots for production logistics: a process optimization model modification. *Proc. Estonian Acad. Sci.*, 2024, **73**(2), 134–141. https://doi.org/10.3176/PROC.2024.2.06

7. Soori, M., Arezoo, B. and Dastres, R. Digital twin for smart manufacturing, a review. *Sust. Manuf. Serv. Econ.*, 2023, **2**, 100017. https://doi.org/10.1016/j.smse.2023.100017
8. Yang, J., Zheng, Y., Wu, J., Wang, Y., He, J. and Tang, L. Enhancing manufacturing excellence with digital-twin-enabled operational monitoring and intelligent scheduling. *Appl. Sci.*, 2024, **14**(15), 6622. https://doi.org/10.3390/APP14156622
9. Park, S., Maliphol, S., Woo, J. and Fan, L. Digital twins in Industry 4.0. *Electronics*, 2024, **13**(12), 2258. https://doi.org/10.3390/ELECTRONICS13122258
10. Tšukrejev, P., Kruuser, K., Gorbachev, G., Karjust, K. and Majak, J. Real-time monitoring of solar modules manufacturing. *Int. J. Eng. Res. Africa*, 2020, **51**, 9–13. https://doi.org/10.4028/WWW.SCIENTIFIC.NET/JERA.51.9
11. Vyskočil, J., Douda, P., Novák, P. and Wally, B. A digital twin-based distributed manufacturing execution system for Industry 4.0 with AI-powered on-the-fly replanning capabilities. *Sustainability*, 2023, **15**(7), 6251. https://doi.org/10.3390/SU15076251
12. Mehrparvar, M., Majak, J. and Karjust, K. A comparative analysis of Fuzzy AHP and Fuzzy VIKOR methods for prioritization of the risk criteria of an autonomous vehicle system. *Proc. Estonian Acad. Sci.*, 2024, **73**(2), 116–123. https://doi.org/10.3176/proc.2024.2.04
13. Mehrparvar, M., Majak, J. and Karjust, K. Effect of aggregation methods in fuzzy technique for prioritization of criteria of automated vehicle system. *AIP Conf. Proc.*, 2024, **2989**, 020011. https://doi.org/10.1063/5.0189323
14. Thakur, P. S., Verma, R. K. and Tiwari, R. Analysis of time complexity of K-means and fuzzy C-means clustering algorithm. *Eng. Math. Lett.*, 2024, **2024**, 4.
15. Liu, Y., Zhang, Z., Jiang, S. and Ding, Y. Application of big data technology combined with clustering algorithm in manufacturing production analysis system. *Decis. Mak.: Appl. Manag. Eng.*, 2024, **7**(1), 237–253. https://doi.org/10.31181/DMAME712024897

Virtuaaltehase mudeli arendamine tehisintellektil põhinevaks tootmise optimeerimiseks

Tõnis Raamets, Kristo Karjust, Aigar Hermaste ja Karolin Kelpman

Uuringus käsitletakse tehisintellektil põhineva analüüsi rakendamist virtuaaltehase mudeli arendamisel eesmärgiga optimeerida tootmisseadmete üldist tõhusust puidutööstusettevõttes. Uuringus kasutati Siemens Plant Simulationi tarkvara, et luua digitaalne kaksik, mis võimaldab tootmisvoogude simulatsiooni ja analüüsi. Lisaks koguti reaalajas andmeid tootmisjuhtimissüsteemi abil, et mudelit täpsustada ja pakkuda dünaamilist ülevaadet tootmisprotsessidest. Kogutud andmete analüüsimiseks rakendati klastrianalüüsi, mis võimaldas tuvastada kitsaskohti ja ressursikasutuse ebatõhusust. Simulatsioonide ja andmepõhiste soovituste põhjal optimeeriti tööjaamade paigutust ja ressursijaotust, mis parandas tootmisvoogude tasakaalu ja vähendas kitsaskohtade esinemist. Tulemused näitavad, et virtuaaltehase mudelite ja tehisintellekti integreerimine aitab tõsta tootmisvoogude tõhusust, vähendada seisakuid ja suurendada investeeringute planeerimise täpsust. Pakutud lähenemine toetab tänapäevase puidutööstuse vajadust paindlike, skaleeritavate ja kulutõhusate lahenduste järele, järgides Industry 5.0 põhimõtteid.

Appendix 8

Publication VIII

Raamets, Tõnis; Karjust, Kristo; Majak, Jüri; Hermaste, Aigar (2025). Implementing an AI-Based Digital Twin Analysis System for Real-Time Decision Support in a Custom-Made Sportswear SME. Applied Sciences, 15, 14, #7952. DOI: 10.3390/app15147952.

applied sciences

Article

Implementing an AI-Based Digital Twin Analysis System for Real-Time Decision Support in a Custom-Made Sportswear SME

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Abstract

Small and medium-sized enterprises (SMEs) in the manufacturing sector often struggle to make effective use of production data due to fragmented systems and limited digital infrastructure. This paper presents a case study of implementing an AI-enhanced digital twin in a custom sportswear manufacturing SME developed under the AI and Robotics Estonia (AIRE) initiative. The solution integrates real-time production data collection using the Digital Manufacturing Support Application (DIMUSA); data processing and control; clustering-based data analysis; and virtual simulation for evaluating improvement scenarios. The framework was applied in a live production environment to analyze workstation-level performance, identify recurring bottlenecks, and provide interpretable visual insights for decision-makers. K-means clustering and DBSCAN were used to group operational states and detect process anomalies, while simulation was employed to model production flow and assess potential interventions. The results demonstrate how even a lightweight AI-driven system can support human-centered decision-making, improve process transparency, and serve as a scalable foundation for Industry 5.0-aligned digital transformation in SMEs.

Keywords: industry 4.0; industry 5.0; digital twin; AI optimization; cluster analysis; production monitoring systems; sustainability; human-centered design; smart factory

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1. Introduction

The digital transformation of manufacturing has progressed rapidly over the past decade, driven by the principles of Industry 4.0, which encompass automation, data exchange, and cyber-physical systems [1,2]. While these advancements have enabled greater efficiency and traceability in large-scale enterprises, small and medium-sized enterprises (SMEs) often encounter structural, financial, and technical obstacles that impede the adoption of advanced digital tools. SMEs involved in small-batch, order-based production frequently operate with fragmented systems, manual data collection, and limited analytical capabilities, which restrict their ability to adapt flexibly to process variations and inefficiencies [3]. The emerging paradigm of Industry 5.0 introduces a complementary perspective, highlighting human-centric, sustainable, and resilient manufacturing systems [4,5]. Instead of replacing humans with automation, Industry 5.0 aims to enhance human capabilities through digital tools that foster interpretability, collaboration, and adaptive decision-making. In this context, digital twins (DTs) have emerged as a key enabler, providing real-time representations of physical systems and establishing a foundation for simulation, optimization, and intelligent feedback through the sensors. Previous research has illustrated the potential of digital twins in high-volume manufacturing, particularly when integrated with artificial intelligence (AI) for predictive modeling and control. However, their application in SMEs remains restricted, primarily due to the complexity and cost of implementation, as well as the need for interpretable, human-aligned outputs [6]. This study is based on the principle that even lightweight, modular digital twin systems, if appropriately designed, can yield significant value in SME environments. The research was conducted as part of the AI and Robotics Estonia (AIRE) initiative, a national competence center at Tallinn University of Technology, that promotes the "test before invest" philosophy, allowing companies to experiment with digital solutions before full-scale deployment [7,8]. The case presented in this paper focuses on a small to medium-sized enterprise (SME) in Estonia that specializes in the manufacture of custom sportswear. The project aimed to implement a real-time digital twin framework built on the Digital Manufacturing Support Application (DIMUSA), enhanced with cluster-based analytics and virtual simulation [9,10]. The aim was to analyze workstation-level data, identify process bottlenecks, and assist production decisions in a format that could be easily interpreted by operators and managers. While digital twins have been widely applied in highly automated, high-volume environments, their practical use in SMEs with flexible, order-based production remains underexplored. Furthermore, this study utilizes a digital shadow, a one-way, real-time data display of production processes, rather than a full bidirectional digital twin, which is more suitable for SME conditions. This study aims to address this gap by implementing and evaluating an AI-supported digital shadow system for real-time decision-making in a custom sportswear SME. The primary objective is to identify and mitigate performance bottlenecks and to enhance responsiveness through simulation-based analysis and clustering of workstation-level performance data. The approach draws inspiration from Lean manufacturing principles and follows a DMAIC-style methodology (Define, Measure, Analyze, Improve, Control), enabling systematic analysis of production inefficiencies in a dynamic SME context [11,12]. The paper begins by outlining the methodological framework, including the system architecture, data sources, and analytical tools used in the study. This is followed by a presentation of the implementation results and insights gained from the pilot case. The discussion then examines the implications of these findings for Industry 5.0 and digitalization in small and medium-sized enterprises. The paper concludes with reflections on lessons learned and suggestions for future research.

2. Materials and Methods

To evaluate the proposed digital twin framework in a real-world production environment, a pilot implementation was carried out at a custom-made sportswear SME in Estonia. This section outlines the structure and components of the solution, including the system architecture, simulation model, data collection methods, and analytical techniques employed for process monitoring and improvement. The approach was developed collaboratively with company stakeholders to ensure minimal disruption and maximum clarity.

2.1. Overview of the Framework

The AI-based digital twin proposed integrates three main components:

(1) real-time production data acquisition and processing,
(2) cluster analysis to detect production patterns and anomalies, and
(3) simulation for validating improvement scenarios and visualizing process behavior.

The solution architecture is illustrated in Figure 1. The central element of the framework is the DIMUSA platform(v1.4, 2024 release), which collects and organizes workstation-level production data via a custom-built Application Programming Interface (API). These data are enriched with contextual information (e.g., product type, shift time) and fed into a clustering module for unsupervised analysis. Simulation models are used both to explore process optimization options and to validate analytical outputs under controlled, repeatable conditions. To ensure systematic and replicable implementation, the approach draws inspiration from Lean manufacturing principles and follows a DMAIC-style methodology (Define, Measure, Analyze, Improve, Control), commonly used in Six Sigma frameworks. In the *Define* phase, the project scope was established in collaboration with stakeholders, focusing on production delays, idle times, and prioritization issues. During the *Measure* phase, real-time data on workstation utilization, cycle durations, and product flow were collected through the DIMUSA interface. The *Analyze* phase employed K-means clustering to classify workstation performance and identify inefficiencies. In the *Improve* phase, simulation experiments with Tecnomatix Plant Simulation tested improvement strategies, such as operator reassignment and task re-sequencing. Finally, the *Control* phase proposed real-time monitoring dashboards based on digital shadow logic, allowing operators and managers to track KPIs and detect deviations early. This structured approach supports informed decision-making and continuous improvement in dynamic SME environments.

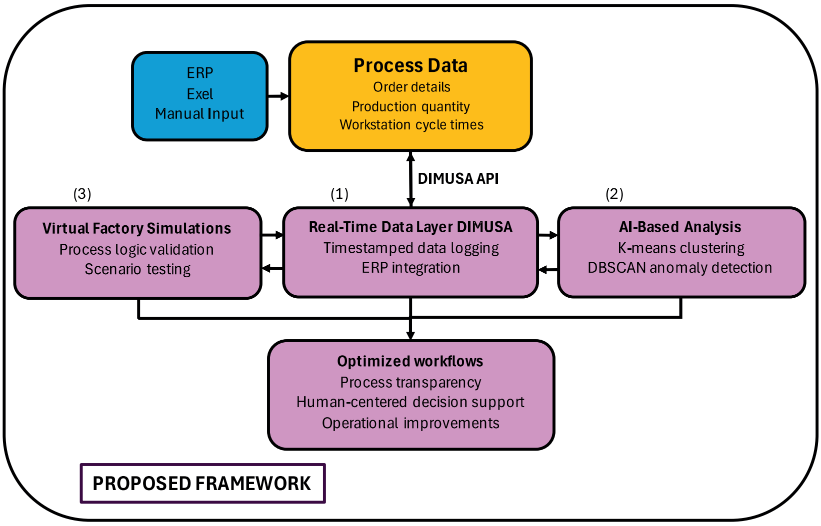

Figure 1. Digital twin framework utilized in pilot SME, integrating real-time data collection and validation, clustering analysis, and simulation for decision support.

2.2. Production Environment Description

The pilot company specializes in small-batch, order-based production. Products are made-to-order, often in varying quantities and combinations, which creates a highly dynamic and variable production flow. The shop floor is divided into functional workstations, including fabric cutting, sewing, printing, and packaging. Before the pilot, the company relied heavily on manual data entry and Excel-based reporting, which limited visibility into real-time performance and made it challenging to detect inefficiencies across workstations [13]. The project aimed to implement a more automated and interpretable system for production monitoring, bottleneck detection, and decision support. The production system is structured into sequential workstation zones, each responsible for specific stages of the process. These include fabric cutting, preparation, printing, and packaging. Figure 2 illustrates the physical layout of the production area, highlighting the relative positions of the workstations involved in the pilot implementation. This layout informed sensor placement, data mapping, and the clustering logic used throughout the study.

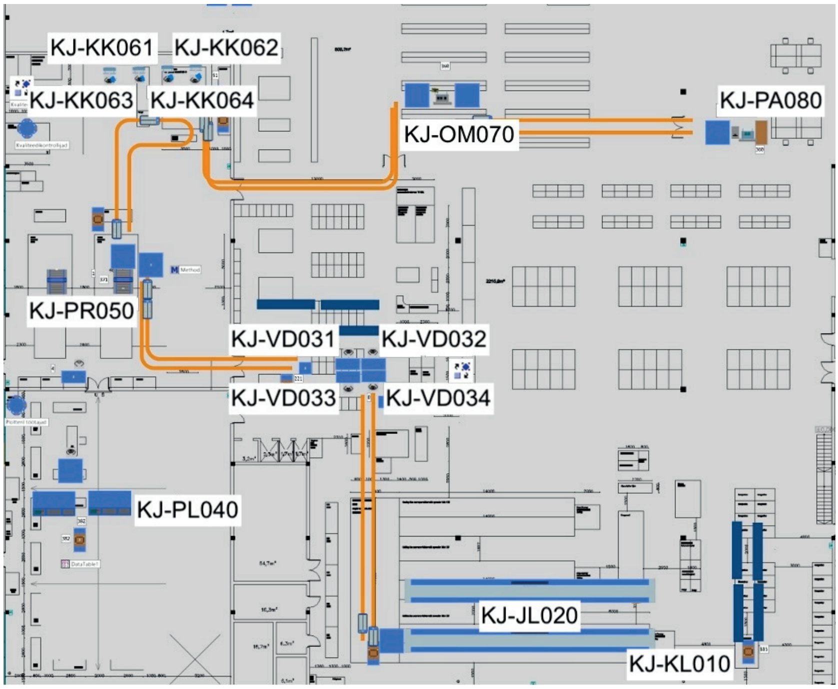

Figure 2. Physical layout of the production area with marked workstation zones used in the pilot implementation.

Table 1 presents the list of workstation codes used in the pilot implementation, along with their corresponding functions and process descriptions. These stations represent the core steps in the company's small-batch production workflow, including material handling, cutting, preparation, pressing, quality control, sewing, and packaging. The coding was used in both data collection and simulation modeling to map digital records to physical operations.

Table 1. Workstation codes, activities, and process descriptions used in the pilot SME.

Code	Workstation/Activity	Process Description
KJ-KL010	Staging and material placement	Marking and transporting material from fabric storage
KJ-JL020	Cutting	Cutting material according to the cutting order
KJ-VD031	White parts preparation	Preparing white fabric parts for pressing
KJ-VD032	White parts preparation	Preparing white fabric parts for pressing
KJ-VD033	White parts preparation	Preparing white fabric parts for pressing
KJ-VD034	White parts preparation	Preparing white fabric parts for pressing
KJ-PL040	Plotter	Preparing press rollers for sublimation
KJ-PR050	Pressing	Pressing visual elements onto white parts
KJ-KK061	Quality control	Inspecting the quality of pressed parts
KJ-KK062	Quality control	Inspecting the quality of pressed parts
KJ-KK063	Quality control	Inspecting the quality of pressed parts
KJ-KK064	Quality control	Inspecting the quality of pressed parts
KJ-OM070	Sewing	Sewing product components
KJ-PA080	Packaging	Packaging finished products

2.3. Virtual Factory Simulation

To complement and validate the analytical logic, a simplified virtual factory simulation model was developed using Siemens Plant Simulation software (2025) [14]. The simulation tested hypotheses generated from clustering analysis, such as workstation overloads, underutilization, and unexpected waiting states, by recreating similar patterns in a controlled environment. This approach allowed the team to assess the causality of observed anomalies and adjust their interpretation of data patterns accordingly. In addition to diagnostic use, the simulation environment enabled the testing of improvement scenarios. Changes such as layout reconfiguration, workstation reordering, and order sequencing modifications were evaluated for their impact on throughput, lead times, and resource balancing [15]. The model mirrored the pilot company's production flow, incorporating dynamic order routing, buffer behavior, and empirically derived cycle time distributions. The simulation ensured that the real-time data architecture and analytics aligned with the actual process behavior before full deployment [16]. Furthermore, it served as an effective communication tool to explain complex process dynamics to non-technical personnel and facilitate decision-making discussions [17]. Figure 3 shows a screenshot of the virtual factory simulation model used during the pilot.

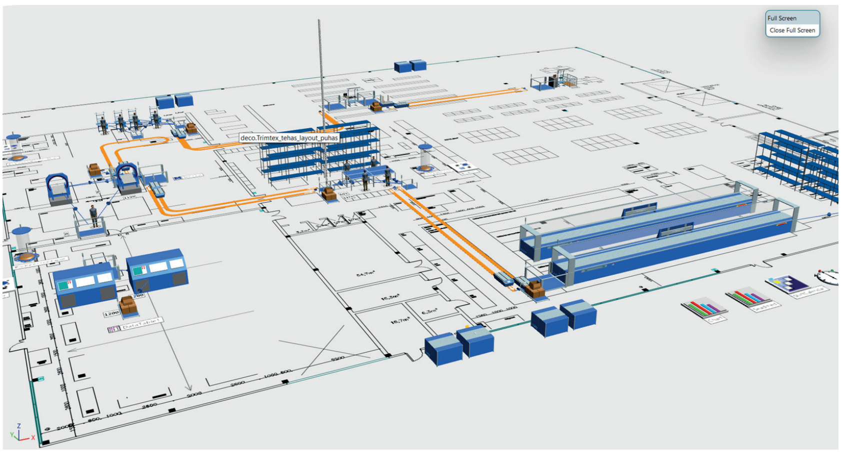

Figure 3. Screenshot of the virtual factory simulation model created in Siemens Plant Simulation to validate data patterns and test production improvement scenarios.

2.4. Data Acquisition and Integration

To support real-time data acquisition in the pilot project, a custom data pipeline was developed by integrating multiple existing and purpose-built components. The company's Enterprise Resource Planning (ERP) system provided information on production orders and routing. At the same time, Microsoft Excel365 (Version 2406, Build 17726.20126), enhanced with Visual Basic for Applications (VBA) macros, was used for manual input and structured formatting. A custom-developed API enabled live data collection from shop-floor terminals and edge devices directly from workstations. All collected data were then centralized and visualized within the DIMUSA platform, serving as the primary hub for both monitoring and analysis. The data captured through this system included the order number, product ID, workstation identifier, and precise timestamps marking the start and end of operations. In cases of interruptions or abnormal events, operators manually entered reason codes and additional contextual information. These structured and timestamped records provided the analytical foundation for performance evaluation and cluster-based analysis in the subsequent stages of the project. Figure 4 illustrates the interface of the DIMUSA system platform, which is used for live monitoring and manual input. The dashboard enabled operators and supervisors to track production progress, identify and visualize the bottlenecks, and contribute relevant context during exception events, enhancing both traceability and interpretability throughout the system.

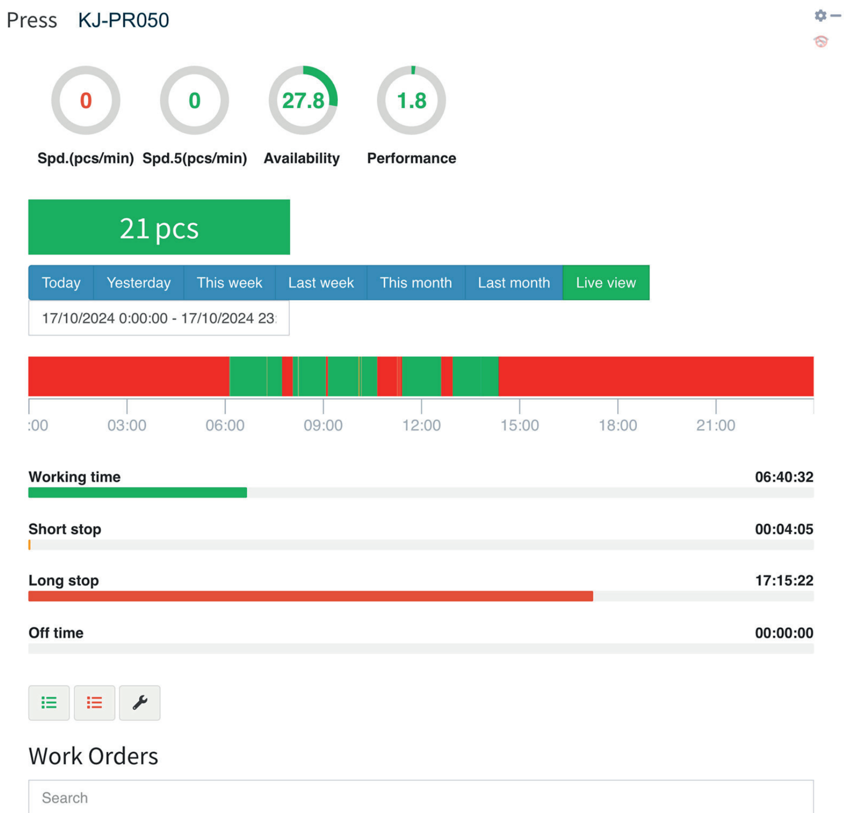

Figure 4. The DIMUSA platform interface is used for real-time workstation data monitoring and operator input collection [9].

2.5. Clustering and Analysis Methods

To analyze workstation performance and identify process inefficiencies, a two-step clustering workflow was applied to the simulation data generated by the virtual factory simulation model. The first step involved outlier filtering using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm [18]. This technique was used to detect and remove anomalous data points, such as unusually long idle periods or sequences of very short cycles, which could distort cluster structure and introduce interpretation bias. In DBSCAN, a point x is considered a core point if it has at least a minimum number of neighboring points (minPts) within a specified radius (ε):

Equation (1).

$$N_\varepsilon(x) = \{y \in D \,||x - y| \leq \varepsilon\}, \text{ and } |N_\varepsilon(x)| \geq \text{minPts} \tag{1}$$

After outlier removal, K-means clustering was applied to categorize the remaining workstation-level data into interpretable operational states [19,20]. This enabled grouping of behaviors into clusters representing conditions such as “stable,” “delayed,” or “high variation.” The goal of K-means is to minimize the total intra-cluster variance:

Equation (2).

$$\min_{C_1,\ldots,C_k} \sum_{j=1}^{k} \sum_{x_i \in C_j} |x_i - \mu_j|^2 \tag{2}$$

where C_j Is the set of data points in cluster j, $\boldsymbol{\mu}_j$ It is the centroid of cluster j, and k is the predefined number of clusters.

The clustering results were visualized to compare simulated performance across workstations over one one-month period. Figure 5 shows the Overall Equipment Effectiveness (OEE) values for each workstation over a month. This time-based view forms the basis for the next clustering analysis, which groups workstations by similar performance patterns. Each line corresponds to a specific workstation, as identified by the layout codes provided in Table 1. Additionally, this summary highlights the top five and bottom five stations based on overall efficiency, helping guide further investigation and process improvements.

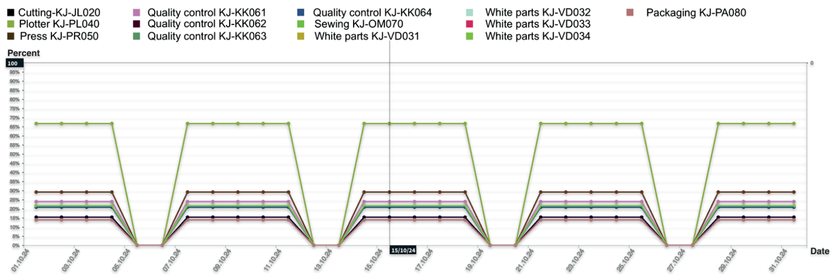

Figure 5. Time-series analysis of workstation OEE based on one-month virtual factory simulation data. The results serve as input for subsequent clustering analysis.

3. Results

The digital twin framework was deployed in the production environment of a custom-made sportswear manufacturing SME over a six-month pilot period. During this time, data were collected from multiple workstations, processed through the DIMUSA platform, and analyzed using a combination of clustering and simulation techniques. The following sections present the key findings derived from this implementation, highlighting patterns in workstation behavior, performance bottlenecks, and the effects of proposed optimization scenarios.

3.1. Production Data Characteristics

Initial input data for the simulation model-including factory layout, selected product types, routing sequences, and partial workstation cycle times, provided by the company in Excel format based on exports from their ERP system. These data formed the baseline for constructing the virtual factory simulation. Excel also served as the company's primary tool for production planning and operational feedback. Throughout the project, this initial dataset was iteratively refined to improve the realism and fidelity of the simulation model. To validate and enrich the simulation inputs, selected production workstations were instrumented with DIMUSA hardware for real-time monitoring. On the plotter workstation, current sensors were successfully used to detect active plotting periods, enabling an accurate view of operational cycles. However, on the heat-based press workstation, current-based monitoring proved ineffective, as the heating system remained continuously powered during the entire shift. To overcome this limitation, a part-counting sensor was installed on the press to identify the start and end of each print cycle by detecting the movement of physical materials. In addition to sensor-based monitoring, a manual reporting phase was conducted during one week of the pilot, during which operators logged task start and completion events via the DIMUSA interface. Although limited in duration, this experiment helped assess data quality and train staff on accurate input procedures. DIMUSA data were collected continuously over a six-month period from selected workstations, while simulation data covered a three-month virtual period. Bidirectional data flow was established between Excel and the DIMUSA platform. Task orders were imported into DIMUSA for execution monitoring, and actual start and end times were exported back to Excel for further analysis. Collected data included equipment usage, cycle time durations, idle intervals, and manually logged exceptions. To ensure reliability, post-processing steps were applied to filter out simulation artifacts, correct manual input errors, and align reported events with equipment-level OEE indicators [21]. Before applying cluster analysis, the dataset was cleaned to improve interpretability and accuracy. Based on the simulation and monitoring results, the plotter and press workstations were selected as focal points for deeper analysis, given their high load, complexity, and integration with both DIMUSA sensors and manual reporting channels. These workstations exhibited the highest OEE scores and output volumes during the monitoring period within one month, as shown in Table 2. Their central role in the company's mini-batch production process, starting from plot file generation to material preparation and pressing, further justified the focus. Table 1 provides a summary of workstation-level KPIs for October 2024, highlighting the relative performance of each monitored station in terms of availability, performance, quality, OEE, Total Effective Equipment Performance (TEEP), and production results.

Table 2. Summary of OEE-related performance metrics for monitored workstations (during October 2024).

Date	Workstation	Availability %	Performans %	Quality %	OEE %	TEEP %	Result/pcs
2024/10	Plotter KJ-PL040	67%	100%	100%	67%	16%	9200
2024/10	Press KJ-PR050	29%	100%	100%	29%	7%	9200
2024/10	Quality control KJ-KK061	24%	100%	100%	24%	6%	2300
2024/10	White parts KJ-VD031	22%	101%	100%	22%	5%	2622
2024/10	White parts KJ-VD032	22%	101%	100%	22%	5%	2622
2024/10	White parts KJ-VD033	21%	101%	100%	22%	5%	2599
2024/10	White parts KJ-VD034	21%	101%	100%	22%	5%	2599
2024/10	Quality control KJ-KK062	21%	100%	100%	21%	5%	2300
2024/10	Quality control KJ-KK063	21%	100%	100%	21%	5%	2300
2024/10	Quality control KJ-KK064	21%	100%	100%	21%	5%	2300
2024/10	Cutting KJ-JL020	15%	100%	100%	15%	4%	20,355
2024/10	Sewing KJ-OM070	14%	100%	100%	14%	3%	9200
2024/10	Packaging KJ-PA080	14%	100%	100%	14%	3%	9200

3.2. Cluster Analysis Results

A clustering-based analytical workflow was applied to the preprocessed production dataset to identify performance patterns and anomalies across workstations. The methodology combined DBSCAN-based prefiltering with K-means clustering to enhance robustness and interpretability. The dataset was first cleaned and normalized. Key performance indicators were selected as clustering features, including OEE, availability, performance, quality, and state durations (produced, off, short, long, and working). Categorical workstation labels were encoded numerically, and timestamps were converted into a consistent datetime format. DBSCAN was used to remove noise and outliers, including negative values and unrealistic cycle durations [22]. Afterward, K-means clustering was applied with k = 5, producing five representative operational states [23]. The most representative workstation and a median timestamp were identified for each cluster to support interpretation. Cluster centroids were computed and enriched with metadata, enabling performance comparison across stations and time windows. Average OEE scores then ranked workstations to identify top and bottom performers, while problematic stations were flagged for deeper investigation. The entire process, from parameter definition to final visualization, followed a structured analysis pipeline [24]. This included feature selection, validation checks, outlier handling (e.g., logarithmic transformations), and cluster labeling. Both the DBSCAN and K-means clustering algorithms were implemented in Python (version 3.12) and integrated into the DIMUSA system as part of its analytical backend. The results were visualized through the DIMUSA dashboard as interactive time-series views and color-coded status overlays, enabling planners and supervisors to identify root-cause opportunities for improvement. The complete clustering workflow is illustrated in Figure 6, which served as the basis for implementing data-driven diagnostics in a live production setting.

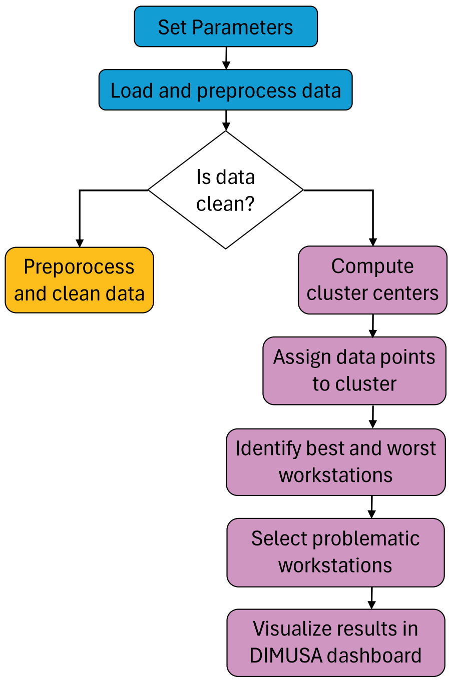

Figure 6. Clustering workflow from data preprocessing to performance visualization.

The clustering results were further visualized using a two-dimensional scatter plot to map the relationship between availability and performance across all monitored workstations. Figure 7 presents the cluster distribution based on the simulation data collected throughout October 2024. Each data point represents the aggregated performance of a workstation for a given time window, with color-coded labels indicating the different stations. The visualized output closely corresponds to the quantitative results shown in Table 1, providing a fast and intuitive overview of workstation utilization. The chart effectively highlights performance disparities, such as the consistently high workload of the plotter and press stations. When large volumes of production data are involved, this type of visual summary can significantly accelerate interpretation by production planners, enabling them to detect trends, anomalies, and bottlenecks with greater clarity and precision. The graph serves as a valuable decision-support tool in daily operations, guiding attention and improvement efforts.

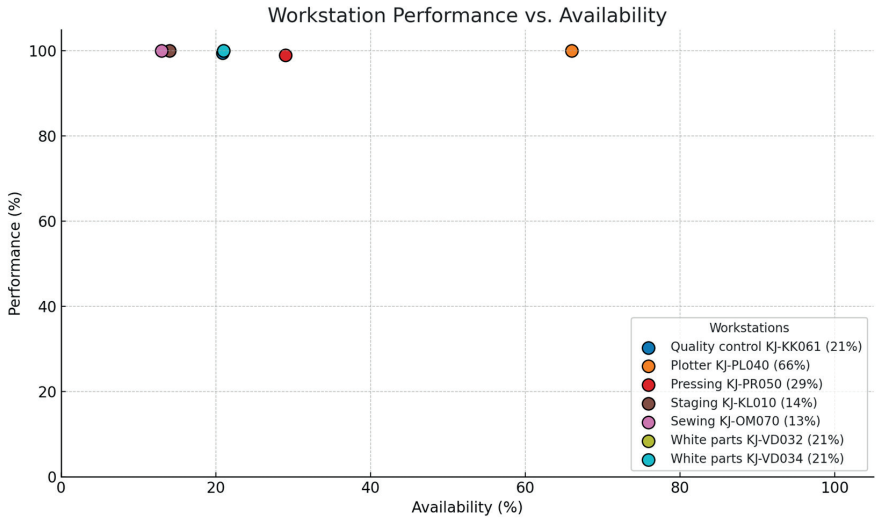

Figure 7. Availability vs. performance plot of clustered workstation data based on virtual factory simulation output from October 2024.

3.3. Identified Bottlenecks and Insights

The analysis centered around the company's use of micro-batches, which represent small, order-specific production batches organized around the output of the plotter. Each micro-batch begins when the operator aggregates a group of print jobs and generates a roll-specific print file [25]. This event initiates a tightly coupled sequence: white fabric components are prepared, aligned with the roll content, and stacked for pressing. The press then operates at a fixed technological speed, processing each roll according to predefined thermal and pressure settings. The micro-batch ends once all units are pressed and transferred to quality control. Early simulation scenarios revealed that this structure, although efficient in principle, relies heavily on precise coordination between workstations [26]. Plotter throughput sets the rhythm, while upstream and downstream stations (preparation and press) must synchronize their activities to avoid idle time or bottlenecks. In particular, white detail preparation exhibited delays in aligning material readiness with roll completion, resulting in repeated idle periods at the press. This issue was validated through real-time measurements. The press workstation exhibited stable operating parameters; however, clusters of idle states often coincided with late material delivery. Conversely, the plotter experienced workload spikes due to variable job grouping and the formation of ad hoc micro-batches. These variations amplified the inconsistency in the downstream flow. To analyze the issue holistically, simulation results were compared with real production data collected through the DIMUSA platform [27]. This cross-validation helped confirm that the observed performance gaps stemmed not from individual workstation inefficiencies but from structural misalignments in micro-batch sequencing. The cluster-based visualization made these patterns explicit, supporting root-cause discussions during daily meetings with team leaders. Overall, the findings emphasized the importance of digital support for batch logic and material readiness, particularly in environments characterized by short-run variability and manual task transitions [28]. The micro-batch logic, described below in

Figure 8, illustrates the tightly coupled flow initiated by the plotter and concluded at the quality control step, underpinning the coordination issues discussed in this section.

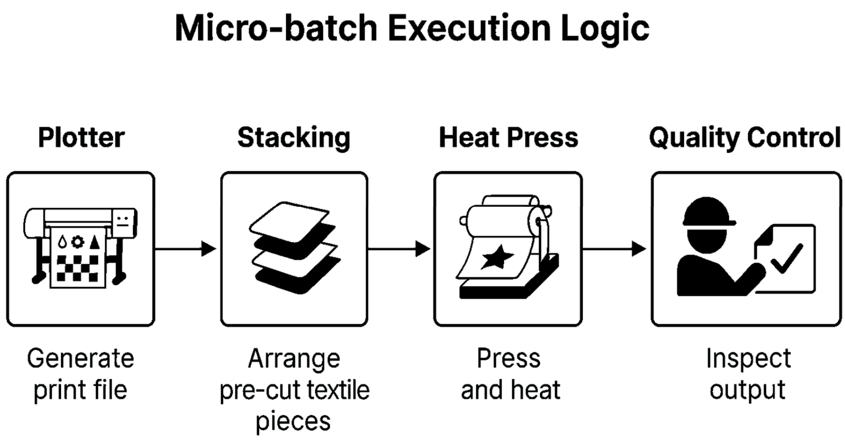

Figure 8. Visual representation of the micro-batch production sequence.

The micro-batch process begins with aggregated order data, which is grouped at the plotter workstation into printable roll files. Each roll considers the printing material and thermal press parameters. Based on the roll content, fabric pieces are pre-cut and stacked in sequence to align with the upcoming press cycle. The thermal press applies heat and pressure to transfer the print onto each aligned fabric layer. The process ends when the printed components are transferred to quality control. This structure ensures a clear production rhythm but also introduces synchronization dependencies between the plotter, cutting, and pressing operations.

3.4. Simulation Validation

To validate the realism and predictive accuracy of the simulation model, a focused comparison was conducted between virtual factory simulation outputs and real production data collected through the DIMUSA system. The validation focused on availability metrics and aimed to identify discrepancies between simulated assumptions and real-world behavior across multiple workstations [29]. Figure 9 presents a direct visual comparison of workstation availability across one selected production day. The upper chart displays the availability values used in the simulation model, derived from baseline process assumptions. Availability represents the share of actual working time relative to a full 8-h shift (480 min), where 100% means uninterrupted operation throughout the shift. The lower chart reflects actual availability as measured by DIMUSA sensors during the same operational window. The contrast between the two layers highlights differences in timing patterns, utilization rates, and workstation coordination. This side-by-side view revealed that simulated data tended to assume more uniform availability across workstations, while real-world data showed greater fluctuation, particularly during shift transitions and material handling events. These findings informed subsequent updates to the simulation model, ensuring more accurate modeling of downtime and micro-delays.

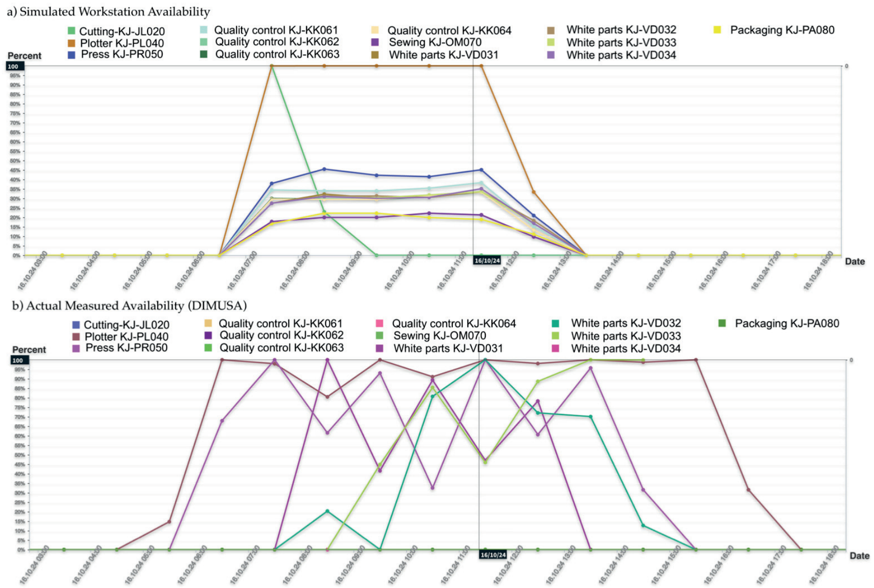

Figure 9. Comparison of workstation availability between (**a**) simulation model assumptions and (**b**) actual DIMUSA measurements for a single production day (16 October 2024).

To further contextualize these observations, the plotter and press workstations were analyzed in detail for two consecutive days-October 16th and 17th. On these days, production was structured around micro-batches, and both sensor data and operator-reported task logs were available. Tables 3 and 4 summarize this cross-validation, comparing timestamps and durations across the simulation, DIMUSA monitoring, and manual reporting systems [30]. The analysis confirmed that while the simulation provided a solid approximation of expected process flows, it occasionally underestimated idle periods and overstated continuity. In contrast, DIMUSA sensor logs revealed nuanced interruptions, particularly in the press workstation, where material readiness and operator interactions had a greater impact than initially modeled. This three-way validation-spanning simulation, sensor feedback, and operator input proved instrumental in refining the digital twin's predictive capacity [31]. By closing the loop between planning and execution, the simulation framework became better aligned with real production rhythms, supporting more effective forecasting and targeted optimization strategies. The methodology demonstrated here is scalable to additional workstations and process types, underscoring the importance of empirical feedback in refining digital twins.

Table 3 presents task-level data from the plotter workstation on 16 October 2024, comparing three sources: manually logged task start and end times by operators, corresponding activity durations from the simulation model, and sensor-based records collected through the DIMUSA system. While the overall timing was similar across data sources, slight deviations were observed in transition gaps between micro-batches. These gaps were better captured by DIMUSA sensors, which identified short but recurring idle periods not reflected in simulation assumptions or manual logs. This highlighted the usefulness of sensor-level granularity in exposing brief disruptions that accumulate into meaningful inefficiencies.

Table 3. Plotter workstation activity on 16 October 2024, based on manually reported task feedback, simulation data, and DIMUSA sensor logs.

Actual execution of work orders (manual input)											
Code	**Workstation**	**Actual start**	**Actual stop**	**Off**	**Short stop**	**Long Stop**	**Working**	**Quantity/m^2**			
Micro-batch-44-025-CAA	Plotter KJ-PL040	16/10/2024 5:56:02	16/10/2024 7:31:21	00:00:00	00:01:12	00:00:00	01:34:07	115.9 m^2			
Micro-batch-44-023-CA	Plotter KJ-PL040	16/10/2024 7:32:18	16/10/2024 8:31:58	00:00:00	00:01:02	00:03:23	00:55:14	73.88 m^2			
Micro-batch-44-034-CAA	Plotter KJ-PL040	16/10/2024 14:33:11	16/10/2024 16:23:18	00:00:00	00:00:00	00:05:04	01:45:01	148.58 m^2			
Micro-batch-44-032-CM	Plotter KJ-PL040	16/10/2024 10:26:16	16/10/2024 12:36:55	00:00:00	00:01:08	00:00:20	02:09:09	164.1 m^2			
Micro-batch-44-028-CK	Plotter KJ-PL040	16/10/2024 8:52:37	16/10/2024 10:21:49	00:00:00	00:00:48	00:00:00	01:28:23	104.03 m^2			
Micro-batch-44-037-CM	Plotter KJ-PL040	16/10/2024 12:37:27	16/10/2024 14:32:58	00:00:00	00:00:44	00:00:00	01:54:46	169 m^2			
			TOTAL:	00:00:00	**0:04:55**	**0:08:49**	**9:46:43**	**775.49 m^2**			
Virtual factory simulation data											
Shift	**Workstation**	**Start**	**End**	**Off**	**Short stop**	**Long Stop**	**Working**	**Quantity/m^2**	**Availability**	**Performance**	**OEE**
17.10.2024	Plotter KJ-PL040	16/10/2024 7:00:00	16/10/2024 15:00:00	00:00:00	**00:00:01**	**02:39:59**	**05:20:00**	400	67%	100%	67%
DIMUSA real-time data											
Shift	**Workstation**	**Start**	**End**	**Off**	**Short stop**	**Long Stop**	**Working**	**Quantity/m^2**	**Availability**	**Performance**	**OEE**
17.10.2024	Plotter KJ-PL040	16/10/2024 6:00:00	16/10/2024 18:00:00	00:00:00	**00:04:55**	**01:56:13**	**09:58:51**	775	83%	0%	0%

Table 4. Press workstation activity on 17 October 2024, based on manually reported task feedback, simulation data, and DIMUSA sensor logs.

Actual execution of work orders (manual input)											
Code	**Workstation**	**Actual start**	**Actual stop**	**Off**	**Short stop**	**Long Stop**	**Working**	**Quantity/m^2**			
Micro-batch-44-025-CAA	Press KJ-PR050	17/10/2024 11:26:31	17/10/2024 12:08:10	00:00:00	00:00:00	00:00:00	00:41:38	115.9 m^2			
Micro-batch-44-023-CA	Press KJ-PR050	17/10/2024 12:09:23	17/10/2024 12:37:29	00:00:00	00:00:00	00:00:40	00:27:25	73.88 m^2			
Micro-batch-44-020-CAA	Press KJ-PR050	17/10/2024 8:34:12	17/10/2024 9:06:07	00:00:00	00:00:00	00:00:34	00:31:20	91.3 m^2			
Micro-batch-44-032-CM	Press KJ-PR050	17/10/2024 9:09:51	17/10/2024 10:05:54	00:00:00	00:00:28	00:00:00	00:55:34	164.1 m^2			
Micro-batch-44-037-CM	Press KJ-PR050	17/10/2024 13:00:30	17/10/2024 13:52:52	00:00:00	00:00:00	00:00:00	00:52:22	169 m^2			
	TOTAL:			00:00:00	**0:00:28**	**0:01:15**	**3:28:21**	**614 m^2**			
Virtual factory simulation data											
Shift	**Workstation**	**Start**	**End**	**Off**	**Short stop**	**Long Stop**	**Working**	**Quantity/m^2**	**Availability**	**Performance**	**OEE**
17.10.2024	Press KJ-PR050	17/10/2024 7:00:00	17/10/2024 15:00:00	00:00:00	00:00:00	05:40:00	02:20:00	400	29%	99.9%	29%
DIMUSA real—time data											
Shift	**Workstation**	**Start**	**End**	**Off**	**Short stop**	**Long Stop**	**Working**	**Quantity/m^2**	**Availability**	**Performance**	**OEE**
17.10.2024	Press KJ-PR050	17/10/2024 6:00:00	17/10/2024 18:00:00	00:00:00	00:04:05	05:15:24	06:40:30	614	56%	4%	2%

Table 4 presents the press workstation data from 17 October 2024, following the same structure. Unlike the plotter, the press exhibited more variation between simulated expectations and actual execution. Several micro-batches experienced delays or extended idle periods between processing steps. In some cases, operator-logged reasons included material unavailability or coordination delays. DIMUSA readings confirmed these delays through prolonged inactive states. The comparison underlined the importance of accounting for coordination dependencies and manual handling variability when calibrating the simulation model. It also reinforced the need for complementary validation layers-manual reporting, real-time monitoring, and simulation achieve an accurate representation of production behavior.

3.5. Impact

In addition to its analytical and planning benefits, the digital twin implementation provided the manufacturing SME with a structured and scalable pathway for transitioning from manual Excel-based production tracking to a real-time, AI-supported monitoring environment [32]. By integrating with the DIMUSA platform, the company gained early visibility into inefficiencies, intuitive visualization of operational states, and improved communication between technical specialists and production staff. The complementary simulation model allowed hypotheses to be tested virtually before applying process changes on the actual shop floor [33]. This reduced implementation risk and increased trust in the insights generated by the analytical pipeline. Simulation results revealed that workstation synchronization, shift transitions, and operator-induced cycle variations can significantly impact overall line performance. This hybrid approach, which combines real-time data collection, clustering-based analytics, and simulation-driven forecasting, exemplifies the AIRE initiative's "test before invest" principle. It enabled a low-risk and phased transition from prototype evaluation to operational deployment, explicitly tailored to the needs and constraints of small-batch, human-centric production environments [34].

4. Discussion

The implementation of an AI–supported digital twin in a small–batch manufacturing environment demonstrated how advanced data analytics and simulation can enhance production understanding without requiring a full–scale digital infrastructure overhaul. While digital twins have been widely studied in high–volume manufacturing and cyber–physical systems, their application in SMEs remains limited. This study contributes to that gap by showing how modular and lightweight solutions, combined with targeted data collection and stakeholder collaboration, can unlock valuable insights without disrupting daily operations. One of the key findings was the importance of timing coordination in short–run production. Unlike traditional mass production, where variability is minimized through volume and standardization, the small–batch model relies on flexibility and human input, making process synchronization more challenging. The use of "micro–batches" as a practical structuring mechanism proved effective, but also exposed the fragility of the system when task sequencing or material preparation was delayed. Clustering revealed recurring inefficiencies that would have been difficult to identify through manual observation or standard key performance indicators (KPIs) alone. In particular, the combined use of DBSCAN and K–means clustering allowed the team to filter out noise, detect state–specific patterns, and highlight the variability in workstation performance. These insights were used to guide process discussions and test improvements virtually, reducing the need for costly trial–and–error adjustments on the production floor. Simulation results aligned with observed bottlenecks, reinforcing the validity of the analytical approach and offering a realistic preview of how even minor adjustments, such as staggered handovers or buffer size changes, could increase throughput. From a broader perspective, the results align with the goals of Industry 5.0, where human–centered decision–making and interpretability are emphasized over full automation. The data visualization features embedded in the DIMUSA platform enabled planners and operators to understand what was happening in the system and why, thereby facilitating more confident and collaborative responses to identified issues. The study also supports the relevance of the "test before invest" approach in SME settings, where experimentation capacity is limited and disruption must be minimized. By leveraging a combination of real–time monitoring and virtual validation, the team bridged the gap between abstract digital strategies and grounded operational improvements. Moreover, while the case focused on a sportswear manufacturer, the same digital twin methodology could be generalized to other domains characterized by small–batch variability, manual processes, and frequent order customization, such as artisanal production, medical device assembly, and high–mix electronics. It is also important to emphasize that this study primarily focused on assessing the conceptual applicability of the framework. While the simulation–based analysis and digital shadow system provided important insights, it is essential to note that this study mainly focused on assessing the conceptual applicability of the framework. The goal was not full operational implementation, but rather identifying critical production inefficiencies that could guide future deployment. Therefore, real–time KPIs and data visualizations were utilized to support collaborative analysis with stakeholders; however, long–term effects, such as ROI, capacity utilization, or sustained performance improvements, will require further integration and ongoing tracking. This approach aligns with the "test before invest" philosophy promoted in SME innovation environments, where experimental validation is a necessary first step toward more reliable implementation. While simulation alone can offer valuable insights into process flows and bottlenecks, its effectiveness relies heavily on predefined assumptions and manual scenario testing. In contrast, integrating AI–based clustering greatly improves this process by automatically identifying patterns, anomalies, and workstation–specific inefficiencies without needing prior hypotheses. The clustering results guided the simulation setup by highlighting where inefficiencies are most likely to happen, enabling more targeted and efficient scenario validation. This synergy between unsupervised AI analysis and simulation fosters a more systematic and data–driven approach to improvement planning. Therefore, while simulation is a powerful tool by itself, combining it with AI analytics speeds up root–cause identification and scenario prioritization, especially in cases of small–batch variability and limited operator capacity. These sectors similarly struggle with synchronization, traceability, and process visibility, making them strong candidates for the application of lightweight digital twin architectures that support human–in–the–loop optimization.

5. Conclusions and Future Work

This study explored the implementation of an AI–enhanced digital twin framework in a real–world small–batch manufacturing environment. The approach combined real–time data acquisition, clustering–based analysis, and simulation modeling to support human–centered decision–making and improve production transparency. The integration of the DIMUSA enabled the automated collection, processing, and visualization of workstation–level performance data, bridging the gap between manual practices and intelligent monitoring. By applying clustering algorithms such as K–means and DBSCAN, the system successfully identified operational states and process anomalies that traditional KPI reporting would have overlooked. These insights helped isolate inefficiencies related to cycle variation, workstation synchronization, and operator–driven fluctuations. In parallel, the use of virtual factory simulation provided a low–risk environment for validating hypotheses and exploring improvements, allowing the company to test and refine operational strategies before applying them in live production. The developed framework emphasized modularity, interpretability, and scalability factors for successful deployment in SMEs with limited digital infrastructure and technical capacity. Beyond technical performance, the solution supported collaborative learning and team engagement by offering accessible visualizations and structured feedback mechanisms. These characteristics resonate strongly with the principles of Industry 5.0, where human involvement, adaptability, and sustainable improvement are prioritized. Future development will focus on expanding system coverage across additional production areas, integrating predictive components, and refining clustering logic through the application of supervised learning techniques. Integration with enterprise systems, such as ERP and Manufacturing Execution System MES platforms, is also planned to ensure seamless data continuity and richer contextual awareness. Longer–term studies could investigate how such systems affect organizational learning, routine adaptation, and continuous improvement within SME environments. The findings of this case study reinforce the conclusion that digital twin technologies, adapted to real–world constraints and deployed incrementally, can offer measurable value even in resource–constrained industrial settings. The key is aligning technology with operational realities and empowering human decision–makers through interpretable, actionable data.

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References

1. Mchirgui, N.; Quadar, N.; Kraiem, H.; Lakhssassi, A. The Applications and Challenges of Digital Twin Technology in Smart Grids: A Comprehensive Review. *Appl. Sci.* **2024**, *14*, 10933. [CrossRef]
2. Derigent, W.; Cardin, O.; Trentesaux, D. Industry 4.0: Contributions of Holonic Manufacturing Control Architectures and Future Challenges. *J. Intell. Manuf.* **2021**, *32*, 1797–1818. [CrossRef]
3. Masood, T.; Sonntag, P. Industry 4.0: Adoption Challenges and Benefits for SMEs. *Comput. Industry* **2020**, *121*, 103261. [CrossRef]
4. Davila-Gonzalez, S.; Martin, S. Human Digital Twin in Industry 5.0: A Holistic Approach to Worker Safety and Well-Being through Advanced AI and Emotional Analytics. *Sensors* **2024**, *24*, 655. [CrossRef] [PubMed]
5. Wang, B.; Zheng, P.; Wang, L.H.; Mourtzis, D. *Human-Centric Smart Manufacturing Towards Industry 5.0*; Springer Nature: Berlin/Heidelberg, Germany, 2025. [CrossRef]
6. Demarchi, M.; Bonello, A.; Francalanza, E.; Rauch, E. A Digital Twin for SMEs in the Context of Industry 5.0. *Procedia CIRP.* **2024**, *126*, 242–247. [CrossRef]
7. Raamets, T.; Karjust, K.; Hermaste, A.; Kelpman, K. Virtual Factory Model Development for AI-Driven Optimization in Manufacturing. *Proc. Est. Acad. Sci.* **2025**, *74*, 228. [CrossRef]

8. Paavel, M.; Karjust, K.; Majak, J. PLM Maturity Model Development and Implementation in SME. *Procedia CIRP.* **2017**, *63*, 651–657. [CrossRef]
9. Snatkin, A.; Karjust, K.; Eiskop, T. Real Time Production Monitoring System in SME. In Proceedings of the Proceedings of the 8th International Conference od DAAAM Baltic Industrial Engineering 19–21st, Tallinn, Estonia, 19–21 April 2012; Tallinna Tehnikaülikooli Kirjastus: Tallinn, Estonia, 2012; pp. 573–578.
10. Ahmed, M.; Seraj, R.; Islam, S.M.S. The K-Means Algorithm: A Comprehensive Survey and Performance Evaluation. *Electron.* **2020**, *9*, 1295. [CrossRef]
11. Sundar, R.; Balaji, A.N.; Satheesh Kumar, R.M. A Review on Lean Manufacturing Implementation Techniques. *Procedia Eng.* **2014**, *97*, 1875–1885. [CrossRef]
12. Daniyan, I.; Adeodu, A.; Mpofu, K.; Maladzhi, R.; Kana-Kana Katumba, M.G. Application of Lean Six Sigma Methodology Using DMAIC Approach for the Improvement of Bogie Assembly Process in the Railcar Industry. *Heliyon* **2022**, *8*, e09043. [CrossRef] [PubMed]
13. de Man, J.C.; Strandhagen, J.O. Spreadsheet Application Still Dominates Enterprise Resource Planning and Advanced Planning Systems. *IFAC-Pap* **2018**, *51*, 1224–1229. [CrossRef]
14. Siemens Software. *Plant Simulation Software*, 2025 version; Siemens AG: Munich, Germany, 2025. Available online: https://plm.sw.siemens.com/en-US/tecnomatix/plant-simulation-software/ (accessed on 2 May 2025).
15. Mahmood, K.; Karjust, K.; Raamets, T. Production Intralogistics Automation Based on 3D Simulation Analysis. *J. Mach. Eng.* **2021**, *21*, 102–115. [CrossRef]
16. Longo, F.; Mirabelli, G.; Solina, V.; Alberto, U.; De Paola, G.; Giordano, L.; Ziparo, M. A Simulation-Based Framework for Manufacturing Design and Resilience Assessment: A Case Study in the Wood Sector. *Appl. Sci.* **2022**, *12*, 7614. [CrossRef]
17. Siderska, J. Application of Tecnomatix Plant Simulation for Modeling Production and Logistics Processes. *Bus. Manag. Educ.* **2016**, *14*, 64–73. [CrossRef]
18. Ram, A.; Jalal, S.; Jalal, A.S.; Kumar, M. A Density Based Algorithm for Discovering Density Varied Clusters in Large Spatial Databases. *Int. J. Comput. Appl.* **2010**, *3*, 1–4. [CrossRef]
19. Cui, J.M.; Liu, J.M.; Liao, Z.Y. Research on K-Means Clustering Algorithm and Its Implementation. In Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013), Hangzhou, China, 22–23 March 2013; Atlantis Press: Dordrecht, The Netherlands, 2013; pp. 1804–1806. [CrossRef]
20. Ahmad, A.; Dey, L. A K-Mean Clustering Algorithm for Mixed Numeric and Categorical Data. *Data Knowl. Eng.* **2007**, *63*, 503–527. [CrossRef]
21. Niekurzak, M.; Lewicki, W. Optimisation of the Production Process of Ironing Refractory Products Using the OEE Indicator as Part of Innovative Solutions for Sustainable Production. *Sustainability* **2025**, *17*, 4779. [CrossRef]
22. Ester, M.; Kriegel, H.P.; Sander, J.; Xu, X. A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD'96), Oregon, Portland, 2–4 August 1996; pp. 226–331.
23. MacQueen, J. Some Methods for Classification and Analysis of Multivariate Observations. In *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*; University of California Press: Berkeley, CA, USA, 1967; pp. 281–297.
24. Xu, R.; Wunsch, D. Survey of Clustering Algorithms. *IEEE Trans. Neural Netw.* **2005**, *16*, 645–678. [CrossRef] [PubMed]
25. Thames, L.; Schaefer, D. Software-Defined Cloud Manufacturing for Industry 4.0. *Procedia CIRP* **2016**, *52*, 12–17. [CrossRef]
26. Becker, T.; Chankov, S.M.; Windt, K. Synchronization Measures in Job Shop Manufacturing Environments. *Procedia CIRP* **2013**, *7*, 157–162. [CrossRef]
27. Jain, S.; Lechevalier, D. Standards Based Generation of a Virtual Factory Model. In Proceedings of the 2016 Winter Simulation Conference (WSC), Washington, DC, USA, 11–14 December 2016; pp. 2762–2773. [CrossRef]
28. ur Rehman, A.; Ramzan, M.B.; Shafiq, M.; Rasheed, A.; Naeem, M.S.; Savino, M.M. Productivity Improvement Through Time Study Approach: A Case Study from an Apparel Manufacturing Industry of Pakistan. *Procedia Manuf.* **2019**, *39*, 1447–1454. [CrossRef]
29. Skoogh, A.; Johansson, B. A Methodology for Input Data Management in Discrete Event Simulation Projects. In Proceedings of the Winter Simulation Conference, Miami, FL, USA, 7–10 December 2008; pp. 1727–1735. [CrossRef]
30. Uhlemann, T.H.J.; Lehmann, C.; Steinhilper, R. The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4. *Procedia CIRP* **2017**, *61*, 335–340. [CrossRef]
31. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in Manufacturing: A Categorical Literature Review and Classification. *IFAC-PapersOnLine* **2018**, *51*, 1016–1022. [CrossRef]
32. Wuest, T.; Weimer, D.; Irgens, C.; Thoben, K.D. Machine Learning in Manufacturing: Advantages, Challenges, and Applications. *Prod. Manuf. Res.* **2016**, *4*, 23–45. [CrossRef]

33. Ferreira, L.P.; Ares, E.; Peláez, G.; Marcos, M.; Araújo, M. A Methodology to Evaluate Complex Manufacturing Systems through Discrete-Event Simulation Models. *Key Eng. Mater.* **2012**, *502*, 7–12. [CrossRef]
34. Matt, D.T.; Modrák, V.; Zsifkovits, H. *Implementing Industry 4.0 in SMEs: Concepts, Examples and Applications*; Springer Nature: Berlin/Heidelberg, Germany, 2021; pp. 1–429. [CrossRef]

Appendix 9

	0	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	190	200	210	220	230	240
Line 1	0	4,1	8,6	13,7	23,6	27,0	27,0	30,8	39,3	40,6	40,8	47,5	57,4	67,2	76,3	78,0	78,0	83,3	93,2	103,2	113,2	123,2	132,6	135,7	135,7
Line 2	0	3,6	6,7	13,2	23,3	27,4	27,4	30,5	37,9	38,4	39,0	46,9	57,0	66,7	76,6	84,6	85,2	85,5	92,8	102,8	112,8	122,8	132,8	142,0	144,7
Line 3	0	3,9	8,7	13,2	23,3	32,9	35,6	35,6	40,2	44,0	44,0	47,2	56,9	66,8	76,8	86,6	95,6	97,1	97,1	102,7	112,7	122,7	132,7	142,7	152,4
Line 4	0	3,9	10,6	13,5	23,4	33,4	43,4	51,1	51,7	52,1	56,3	56,6	57,5	65,5	75,3	85,3	90,7	90,7	92,3	101,3	111,3	121,3	131,3	141,3	150,4

Appendix 10

id	Beacon	Anchor start	Anchor end	Start	Stop	Time	Speed m/s	Speed m/min	Disance
99tere	Robot	1007	1029	23/03/2022 10:49:59	23/03/2022 10:50:53	00:00:53	0.79	47.3	42.18
98tere	Robot	1009	1007	23/03/2022 10:49:29	23/03/2022 10:49:59	00:00:30	0.19	11.33	5.79
97tere	Robot	1135	1009	23/03/2022 10:46:35	23/03/2022 10:49:29	00:02:54	0.7	42.26	122.68
96tere	Robot	1038	1135	23/03/2022 10:44:39	23/03/2022 10:46:35	00:01:55	0.84	50.6	97.18
95tere	Robot	1029	1038	23/03/2022 10:43:57	23/03/2022 10:44:39	00:00:42	0.66	39.66	28.14
94tere	Robot	1007	1029	23/03/2022 10:43:06	23/03/2022 10:43:57	00:00:50	0.83	49.57	42.13
						00:06:21	0.76		
93tere	Robot	1009	1007	23/03/2022 10:40:31	23/03/2022 10:43:06	00:02:35	0.03	2.1	5.43
92tere	Robot	1135	1009	23/03/2022 10:38:02	23/03/2022 10:40:31	00:02:28	0.82	49.27	121.94
91tere	Robot	1038	1135	23/03/2022 10:36:05	23/03/2022 10:38:02	00:01:57	0.83	49.77	97.25
90tere	Robot	1029	1038	23/03/2022 10:35:25	23/03/2022 10:36:05	00:00:39	0.71	42.55	28.16
89tere	Robot	1007	1029	23/03/2022 10:33:59	23/03/2022 10:35:25	00:01:26	0.49	29.24	42.16
						00:06:30	0.71		289.51
88tere	Robot	1009	1007	23/03/2022 10:33:31	23/03/2022 10:33:59	00:00:27	0.19	11.67	5.3
87tere	Robot	1135	1009	23/03/2022 10:30:50	23/03/2022 10:33:31	00:02:41	0.76	45.34	122.05
86tere	Robot	1038	1135	23/03/2022 10:29:00	23/03/2022 10:30:50	00:01:49	0.89	53.11	97.13
85tere	Robot	1029	1038	23/03/2022 10:28:20	23/03/2022 10:29:00	00:00:39	0.71	42.53	28.2
84tere	Robot	1007	1029	23/03/2022 10:27:33	23/03/2022 10:28:20	00:00:47	0.88	53.1	42.14
						00:05:56	0.81		

Appendix 11

prodStat 2024-03-22 13-43-48														
Date	Workstation	Avail. %	Perf. %	Qual. %	OEE %	TEEP %	Result	Productivity	Op. active	Off time	Short stop	Long Stop	Working time	Total time
2024/01/01 08:00	Järkamissaag	2.97	102.8	100	3.06	3.08	11	6.17	00:00:00	00:00:00	00:00:00	00:58:12	00:01:48	01:00:00
2024/01/01 08:00	Nelikanthöövel	3.44	104.84	100	3.61	3.63	13	6.29	00:00:00	00:00:00	00:00:00	00:57:55	00:02:05	01:00:00
2024/01/01 08:00	CNC aknakeskus	100	100.6	100	100.6	100.6	134	2.23	00:00:00	00:00:00	00:00:00	00:00:00	01:00:00	01:00:00
2024/01/01 08:00	Immutusprits	66.61	99.93	100	66.57	66.58	133	3.33	00:00:00	00:00:00	00:20:02	00:00:00	00:39:58	01:00:00
2024/01/01 08:00	Profiillihv	66.72	99.77	100	66.57	66.59	133	3.32	00:00:00	00:00:00	00:19:57	00:00:00	00:40:03	01:00:00
2024/01/01 08:00	Kruntimine	55	100	100	55	55.01	33	1	00:00:00	00:00:00	00:27:00	00:00:00	00:33:00	01:00:00
2024/01/01 08:00	Värvimine 1	0	0	100	0	0	0	0	00:00:00	00:00:00	00:00:00	01:00:00	00:00:00	01:00:00
2024/01/01 08:00	Värvimine 2	0	0	100	0	0	0	0	00:00:00	00:00:00	00:00:00	01:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 1	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 2	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 3	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 4	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 5	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 6	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 7	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 8	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Klaasimine 9	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 1	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 2	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 3	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 4	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 5	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 6	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 7	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Komplekteerimine 8	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Pakkimine	0	0	100	0	0	0	0	00:00:00	01:00:00	00:00:00	00:00:00	00:00:00	01:00:00
2024/01/01 08:00	Koostamine 1	93.33	89.29	100	83.33	83.33	5	0.09	00:00:00	00:00:00	00:04:00	00:00:00	00:56:00	01:00:00
2024/01/01 08:00	Koostamine 2	93.33	89.29	100	83.33	83.33	5	0.09	00:00:00	00:00:00	00:04:00	00:00:00	00:56:00	01:00:00
2024/01/01 08:00	Koostamine 3	92	108.7	100	100	100	6	0.11	00:00:00	00:00:00	00:04:48	00:00:00	00:55:12	01:00:00
2024/01/01 08:00	Koostamine 4	93	89.61	100	83.33	83.36	5	0.09	00:00:00	00:00:00	00:04:11	00:00:00	00:55:49	01:00:00
2024/01/01 08:00	Koostamine 5	92	108.7	100	100	100	6	0.11	00:00:00	00:00:00	00:04:48	00:00:00	00:55:12	01:00:00
2024/01/01 08:00	Koostamine 6	92	108.7	100	100	100	6	0.11	00:00:00	00:00:00	00:04:48	00:00:00	00:55:12	01:00:00

Curriculum vitae

1. Personal data

Name:	Tõnis Raamets
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2. Contact information

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3. Education

2021–2026	Tallinn University of Technology, School of Engineering, Mechanical Engineering program, Production engineering and robotics, PhD studies
2005–2025	Tallinn University of Technology, Faculty of Mechanical Engineering, Industrial engineering and management, MSc
2002–2005	Võru County Education and Technology Centre, Metal Processing, applied higher education

4. Language competence

Estonian:	Native speaker
Russian:	Intermediate level
English:	Fluent

5. Professional employment

2021–	Tallinn University of Technology, Faculty of Engineering, Department of Mechanical and Industrial Engineering, PhD student-junior researcher
2018–2021	OÜ IMECC, Development Engineer (0.50)
2018–2021	Tallinn University of Technology, Faculty of Engineering, Department of Mechanical and Industrial Engineering, Engineer (0.50)
2009–2018	Silwi Autoehituse AS, Member of the Board
2007–2009	Silwi Autoehituse AS, Production Manager
2006–2007	Silberauto AS, Product Developer
1998–2005	AS Silberauto Tartu (AV-Tristar), Maintenance Engineer

6. Field of research

- ETIS RESEARCH FIELD: 4. Natural Sciences and Engineering; 4.13. Mechanical Engineering, Automation Technology and Manufacturing Technology
- CERCS RESEARCH FIELD: T125 Automation, robotics, control engineering

7. Honours and awards

- Securing the honorary II place in the Tallinn University of Technology Development Work of the Year 2020 is a testament to the significance of our research in the field of manufacturing and robotics, “Smart Manufacturing and Digital Twins: Self- Moving Robot Vehicle Boxbot in Production Logistics”, K. Karjust, R. Sell, T. Otto, M. Eerme, M. Pärn, V. Kuts, H. Pikner, T. Velsker, M. Kirs, J. Nõu, E. Malayjerdi, T. Raamets, A. Hermaste, K. Mahmood

8. Defended theses

- 2020, Production Logistics Automation in the Chemistry and Food Industry, MSc, Supevisor K. Karjust, Tallinn University of Technology School of Engineering, Department of Mechanical and Industrial Engineering.
- 2005, Development of the technology for manufacturing pneumatic valve part D:901346 based on AS Tarkon, supervisor M.Raamets, Võru County Education and Technology Centre

9. Scientific work
Papers

1. Matsulevitš, Johannes; Majak, Jüri; Eerme, Martin; Sarkans, Martinš; Dunajeva, Olga; Kristjuhan-Ling, Kadri; Raamets, Tõnis; Kekšin, Vjatšeslav (2025). Human-robot interaction: a conceptual framework for safety/risk analysis. Proceedings of the Estonian Academy of Sciences, 74 (2), 137−142. DOI: 10.3176/proc.2025.2.09.
2. Raamets, T.; Karjust, K.; Hermaste, A.; Kelpman, K. (2025). Virtual factory model development for AI-driven optimization in manufacturing. Proceedings of the Estonian Academy of Sciences, 74 (2), 228−233. DOI: 10.3176/proc.2025.2.26.
3. Karjust, Kristo; Mehrparvar, Marmar; Kaganski, Sergei; Raamets, Tõnis (2025). Development of a Sustainability-Oriented KPI Selection Model for Manufacturing Processes. Sustainability, 17 (14), #6374. DOI: 10.3390/su17146374.
4. Raamets, Tõnis; Karjust, Kristo; Majak, Jüri; Hermaste, Aigar (2025). Implementing an AI-Based Digital Twin Analysis System for Real-Time Decision Support in a Custom-Made Sportswear SME. Applied Sciences, 15, 14, #7952. DOI: 10.3390/app15147952.
5. Raamets, T., Majak, J., Karjust, K., Mahmood, K., Hermaste, A. (2024). Autonomous mobile robots for production logistics: a process optimization model modification. Proceedings of the Estonian Academy of Sciences, 73 (2), 134−141. DOI: 10.3176/proc.2024.2.06.
6. Raamets, Tõnis; Majak, Jüri; Karjust, Kristo; Mahmood, Kashif; Hermaste, Aigar (2024). Development of Process Optimization Model for Autonomous Mobile Robot Used in Production Logistics. Modern Materials And Manufacturing 2023: Tallinn, Estonia, 2-4 May 2023. Ed. Karjust, Kristo; Kübarsepp, Jakob. New York: AIP Publishing, #020008. (AIP Conference Proceedings; 2989). DOI: 10.1063/5.0189299.

7. Moor, Madis; Pakkanen, Jarkko; Raamets, Tõnis; Mahmood, Kashif; Riives, Jüri (2024). Industrial Data Analytics in Manufacturing Shop Floor Level. AIP Conference Proceedings, 2989/1: Modern Materials and Manufacturing 2023, Tallinn, Estonia, 2-4 May 2023. Ed. Karjust, Kristo; Kübarsepp, Jakob. New York: AIP Publishing, #030006. DOI: 10.1063/5.0189502.
8. Mahmood, K.; Karjust, K.; Raamets, T. (2021). Production Intralogistics Automation Based on 3D Simulation Analysis. Journal of Machine Engineering, 21 (2), 102−115. DOI: 10.36897/jme/137081.
9. Golova, J.; Mahmood, K.; Raamets, T. (2021). Simulation based Performance Analysis of Production Intralogistics. IOP Conference Series Materials Science and Engineering, 1140 (1), #012026. DOI: 10.1088/1757-899X/1140/1/012026.
10. Raamets, T.; Karjust, K.; Hermaste, A.; Mahmood, K. (2021). Planning and Acquisition of Real-Time Production Data Through the Virtual Factory in Chemical Industry. <i>Proceedings of the ASME 2021, 2B: Advanced Manufacturing: International Mechanical Engineering Congress and Exposition IMECE2021, November 1–5, 2021 Virtual (Online), USA..</i> ASME Digital Collection, V02BT02A017. DOI: 10.1115/IMECE2021-73080.

Elulookirjeldus

1. Isikuandmed

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3. Haridus

2021–2026	Tallinna Tehnikaülikool, Inseneriteaduskond, Mehhanotehnika, doktoriõpe
2005–2025	Tallinna Tehnikaülikool, Inseneriteaduskond, Tootearendus ja tootmistehnika, Msc
2002–2005	Võrumaa Haridus- ja Tehnoloogiakeskus, Metallide töötlemine, Rakenduskõrgharidus

4. Keelteoskus

Eesti keel:	Emakeel
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Inglise keel:	Kõrgtase

5. Teenistuskäik

2021–	Tallinna Tehnikaülikool, Inseneriteaduskond, Mehaanika ja tööstustehnika instituut, doktorant-nooremteadur
2018–2021	OÜ IMECC, Arendusinsener (0,50)
2018–2021	Tallinna Tehnikaülikool, Inseneriteaduskond, Mehaanika ja tööstustehnika instituut , Insener (0,50)
2009–2018	Silwi Autoehituse AS, Juhatuse liige
2007–2009	Silwi Autoehituse AS, Tootmisjuht
2006–2007	Silberauto AS, Tootearendaja
1998–2005	AS Silberauto Tartu (AV-Tristar), Hooldusinsener

6. Teadustöö põhisuunad

- ETIS VALDKOND: 4. Loodusteadused ja tehnika; 4.13. Mehhanotehnika, automaatika, tööstustehnoloogia
- CERCS VALDKOND: T125 Automatiseerimine, robootika, juhtimistehnika

7. Autasud

- Aukiri Tallinna Tehnikaülikooli aasta arendustöö 2020 II koht, „Nutikas tootmine ja digitaalsed kaksikud: Iseliikuv robotsõiduk Boxbot tootmise logistikas", K. Karjust, R. Sell, T. Otto, M. Eerme, M. Pärn, V. Kuts, H. Pikner, T. Velsker, M. Kirs, J. Nõu, E. Malayjerdi, T. Raamets, A. Hermaste, K. Mahmood

8. Kaitstud lõputööd

- 2020, Tootmislogistika automatsiseerimine keemia- ja toiduainetööstuses, Msc, juhendaja Prof. Kristo Karjust, Tallinna Tehnikaülikool, Mehaanika ja tööstustehnika instituut.
- 2005, Pneumoventiili detaili D:901346 valmistamise tehnoloogia väljatöötamine AS Tarkon baasil, juhendaja M. Raamets, Võrumaa Haridus- ja Tehnoloogiakeskus

9. Teadustegevus

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