DOCTORAL THESIS

A Methodology for Designing Reconfigurable and Integrated Robotic Systems

Madis Moor

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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.

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Ümberseadistatavate ja integreeritud robotsüsteemide arenduse metoodika

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List of Publications

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

I 1.1 **Moor, M**.; Vaher, K.; Riives, J.; Kangru, T.; Otto, T. (2021). Modern Robot Integrated Manufacturing Cell According to the Needs of Industry 4.0. Proceedings of the Estonian Academy of Sciences, 70 (4), 407−412. DOI: 10.3176/proc.2021.4.06.

II 3.1 **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.

III 1.1 **Moor, M.**; Sarkans, M.; Kangru, T.; Otto, T.; Riives, J. (2024). AI Functionalities in Cobot-Based Manufacturing for Performance Improvement in Quality Control Application. Journal of Machine Engineering, 24, 5−16. DOI: 10.36897/jme/189169.

IV 3.1 Kangru, T.; Mahmood, K.; Otto, T.; **Moor, M.**; Riives, J. (2020). Knowledge-Driven Based Performance Analysis of Robotic Manufacturing Cell for Design Improvement. Proceedings of the ASME 2020, Volume 6: Design, Systems, and Complexity: International Mechanical Engineering Congress and Exposition IMECE2020, USA, Portland, 16.11.2020. The American Society of Mechanical Engineers, V006T06A032. DOI: 10.1115/IMECE2020-23541.

V 1.1 Kangru, T.; **Moor, M.**; Rudz, A.; Jänes, A. (2024). Reconstructing a Manufacturing Laboratory to a Learning Factory: a TTK UAS Case Study. Journal of Machine Engineering, 24 (3), 133−140. DOI: 10.36897/jme/191243.

Other publications:

VI 1.2 **Moor, M.**; Sarkans, M.; Riives, J.; Otto, T.; Vañó, J. M. (2024). Methodology for Reconfigurable Cobot-Based Quality Control System for SME Production. International Journal of Engineering and Technology (IJET), 16 (2), 113−119. DOI: 10.7763/IJET.2024.V16.1265.

Publications appear in the appendix 1.

Author's Contribution to the Publications

Contribution to the papers in this thesis are:

I Publication I: the author proposed the research topic and defined the study's scope. He analysed the down-scaled production system to isolate core processes, equipment constraints and software requirements for deploying cyber-physical architectures in SME manufacturing. Additionally, the author developed the comprehensive schematic diagrams of the proposed framework, drafted the manuscript, and coordinated the submission process.

II Publication II: the author defined the research objectives and led the real-time data collection from industrial equipment during the case study phase. He performed the production data analysis and formulated the subsequent simulation scenarios for the virtual validation of the process. The author was also responsible for composing the manuscript and presenting the findings at the international conference.

III Publication III: building upon the methodological framework established in Publication VI, the author initiated the research topic and led the development and integration process of robotic cell for performance improvement in quality control application. He contributed to the development of modular programming structures and the training machine vision models. Furthermore, he acted as the primary composer of the manuscript and presented the publication at the conference.

IV Publication IV: the author contributed to the state-of-the-art literature review and provided input for the development and mapping of the manufacturing use-case scenarios.

V Publication V: the author contributed to the literature review, supported the execution and methodology of the learning factory framework, and presented the co-authored publication at the conference.

Other publications:

VI Publication VI: serving as the foundational study for the collaborative quality control unit, the author was the primary contributor to the research design, problem formulation, and the development of reconfiguration methodology for SME production unit. He designed the smart fixture for the legacy robotic cell, assisted in the mechanical assembly of the experimental testbed, drafted the majority of the manuscript, and managed the collaborative editing process between co-authors before presenting the paper at the conference.

Abbreviations

AI	Artificial Intelligence
AM	Advanced Manufacturing
CBQC	Cobot-Based Quality Control
CPS	Cyber-Physical Systems
CPPS	Cyber-Physical Production Systems
DES	Discrete Event Simulation
DOF	Degrees of Freedom
DT	Digital Twin
ERP	Enterprise Resource Planning
EU	European Union
HMLV	High-Mix, Low-Volume
HRC	Human-Robot Collaboration
I4.0	Industry 4.0
I5.0	Industry 5.0
IIoT	Industrial Internet of Things
ISO	International Organization for Standardization
KBE	Knowledge-Based Engineering
KPI	Key Performance Indicator
M2M	Machine-to-Machine
MES	Manufacturing Execution Systems
ML	Machine Learning
MSD	Manufacturing System Design
MQTT	Message Queuing Telemetry Transport
MV	Machine Vision
OEE	Overall Equipment Effectiveness
OPC UA	Open Platform Communication Unified Architecture
PEM	Product Evaluation Matrix
PLC	Programmable Logic Controller
RMS	Reconfigurable Manufacturing System
RQ	Research Question
SME	Small and Medium-sized Enterprise

Explanations of abbreviations used in the thesis—the table.

Introduction

This introductory chapter establishes the conceptual, methodological, and industrial framework of the entire doctoral dissertation, delineating the evolutionary transition from rigid automation to adaptive, human-centric manufacturing systems. As the global production landscape transitions towards the Industry 5.0 (I5.0) paradigm, the necessity to reconcile high-level digital sophistication with the practical constraints of existing infrastructure has become a critical research frontier. The primary focus is placed on the brownfield reality of Small and Medium-sized Enterprises (SMEs), where the integration of legacy systems into modern high-mix, low-volume (HMLV) production cycles remain a critical industrial bottleneck.

To systematically address these challenges, the thesis establishes a comprehensive research trajectory. It begins by investigating the fundamental research gaps and reviewing the standard industrial taxonomies of Cyber-Physical Production Systems (CPPS), Reconfigurable Manufacturing Systems (RMS), and Human-Robot Collaboration (HRC). Upon this theoretical foundation, the core scientific contribution is introduced: a formalized decision-making methodology utilizing a Product Evaluation Matrix (PEM) synchronized with real-time shop-floor metrics to act as semi-automated triggers for system reconfiguration.

These frameworks are subsequently transitioned into practical industrial environments through multi-stage experimental validations – utilizing Digital Twin simulations and physical deployments, including industrial data tracking setups and a cobot-based quality control (CBQC) use-case. By seamlessly linking theoretical modelling with validated physical realizations, this dissertation provides a strategic roadmap ensuring a clear understanding of how smart, reconfigurable, and vision-assisted technologies can be systematically deployed to maximize the utility of legacy assets while fostering long-term industrial resilience and inclusivity.

Consequently, the remainder of this introductory chapter outlines the fundamental research background, identifies current gaps, and analyses the recent development trends that are reshaping the manufacturing field. It proceeds to define the specific objectives and Research Questions (RQ) guiding this study, ultimately mapping them against the targeted research tasks and publications. By synthesizing theoretical rigor with industrial applicability, this structured overview establishes a cohesive foundation for the subsequent chapters, ensuring a transparent transition from preliminary problem formulation to empirically validated cyber-physical deployments.

1.1 Background and Research Gaps

SMEs constitute the backbone of the European Union's (EU) industrial economy, representing approximately 99.8% of all businesses and providing most of the private-sector employment. While the ratio between the amount of companies is vast, the share between SMEs and large companies is 65.1% to 34.9%. (European Commission, 2025). According to the European Commission’s SME Strategy, the digital transformation and modernization of these entities are critical for maintaining Europe’s long-term global competitiveness (European Commission, 2020). Concurrently, the manufacturing sector is facing an unprecedented demographic challenge; studies by Eurofound indicate that 39% of EU manufacturing enterprises report production limitations due to labour shortages (Eurofound & Cedefop, 2020). This trend aligns with United Nations projections, which predict a reduction of up to 95 million workers in Europe by 2050

(United Nations, 2019). This economic backdrop creates a necessity for an accelerated transition toward Industry 4.0 (I4.0) principles, centred on Cyber-Physical Systems (CPS) – integrated systems where computational algorithms and physical processes are networked and operate in synchrony.

To evaluate the empirical readiness and current landscape of this digital transformation across different enterprise scales, it is essential to analyse the real-world adoption rates of advanced automated technologies. In this context, Figure 1 underscores the systemic digital divide within the European industrial economy by detailing the utilization of specific artificial intelligence applications, providing a statistical baseline that illustrates the asymmetric maturity between large corporations and small businesses.

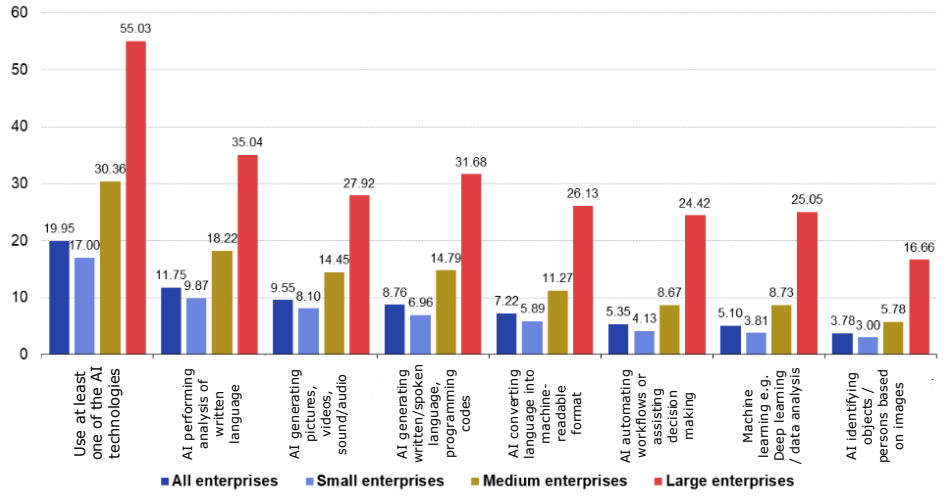


Figure 1. Enterprises using AI by type and size in EU 2025 (Eurostat, 2025)

Despite the evident benefits of automation, the technological advancement of many SMEs is systematically hindered by a reliance on legacy robotic systems. According to International Organization for Standardization ISO 8373 standard and International Federation of Robotics (IFR), an industrial robot is defined as an automatically controlled, reprogrammable mechanism with a degree of autonomy to perform locomotion, manipulation or positioning (International Federation of Robotics, 2026). When such manipulators are integrated with end-effectors, sensors and auxiliary machinery to execute complex workflows, they form a robot cell, designed to automate specific manufacturing task (Lakshminarayanan et al., 2020).

This thesis is concentrated on existing machinery and robotic cells that are functionally operational but lack the necessary data connectivity to communicate with cloud-based platforms. Guerreiro and Lins emphasize that while retrofitting is more economically viable than total equipment replacement, there is a distinct lack of standardized frameworks for integrating legacy sensors with cloud analytics (Guerreiro et al., 2017). Furthermore, Mittal and Singh point out that existing Industry 4.0 implementation models are often overly complex and tailored for large corporations, leaving SMEs without a practical methodology that accounts for their limited resources and heterogeneous equipment landscapes (Singh et al., 2025).

In the context of industrial manufacturing, a brownfield environment refers to an existing production facility operating with established physical infrastructure and functional legacy machinery, where digitalization is achieved by retrofitting cyber-physical capabilities rather than deploying newly built installations (Etz et al., 2020; Tran et al., 2022). This operating context creates distinct integration bottlenecks across small and medium-sized enterprises.

The first significant research gap emerges in the absence of systemic reconfiguration methodologies. Although Reconfigurable Manufacturing Systems are theoretically defined as systems designed for rapid changes in structure to adjust capacity and functionality, their application at the robotic cell level within SME environments has been insufficient. Koren et al. note that while RMS principles are essential for future trends, the design tools for their execution are still maturing (Koren et al., 2018). It is common that scientific literature focuses primarily on large-scale systems, neglecting the logic of rapid reconfiguration at the individual robot-cell level – a necessity for HMLV production.

A second critical area of research concerns the synchronization of Digital Twins (DT) with physical reality. As a real-time virtual representation of a physical object, the DT offers immense potential for process optimization. However, Tao et al. highlight that bidirectional data exchange and real-time synchronization between legacy devices and digital models remain a primary technological bottleneck (Tao et al., 2018). For SMEs, this means a lack of reliable methods to validate new workflows in a virtual environment before physical implementation, which is crucial for minimizing downtime.

Finally, there is a notable gap in the implementation logic of perception-based functions on the shop floor, such as Machine Vision (MV) and adaptive control. The literature documents the transformation potential attributed to AI-based methods in industry (Javaid et al., 2022), while Villani and Xiong argue that the complexity of programming such systems often requires specific expertise that average manufacturing companies lack (Villani et al., 2018; Xiong et al., 2019). The limiting factor for SMEs is therefore not the availability of the perception capability itself, which is already commercially available and mature, but the absence of modular and simplified control structures that would make it configurable and maintainable by shop-floor personnel. This dissertation addresses these gaps by proposing an integrated reconfiguration methodology that unites legacy systems, data analytics, and DT into a unified framework tailored to the needs of SME manufacturing.

To provide a precise scientific focus, this dissertation delineates and addresses three interconnected research gaps that currently limit the evolution of SME brownfield manufacturing:

- *Research Gap 1: The absence of formalized, low-cost reconfiguration methodologies specifically tailored for individual, heterogeneous legacy robot cells in brownfield SME environments, leaving a critical gap between high-level theoretical frameworks and floor-level hardware constraints.*
- *Research Gap 2: The persistent technological bottleneck of achieving real-time, bidirectional data exchange and deterministic synchronization between rigid legacy production equipment and virtual validation environments by using Digital Twins.*
- *Research Gap 3: The lack of modular, simplified software structures and standardized validation metrics that would allow resource-constrained SMEs to integrate automated machine vision features and safe Human-Robot*

Collaboration (HRC) without requiring specialized, high-level coding expertise.

1.2 New Development Trends

The manufacturing landscape is currently transitioning from purely efficiency-driven automation toward the principles of I5.0 and Advanced Manufacturing (AM). This shift emphasizes a human-centric approach, where technology serves to augment human capabilities rather than replace them, and focuses on the resilience of production systems. A dominant trend in this context is cyber-physical retrofitting, which allows SMEs to achieve high-level digitalization without the ecological and financial need of replacing functional machinery. Lins and Oliveira et al. highlight that retrofitting legacy assets with smart sensors and edge computing is a cornerstone of sustainable industrial evolution, enabling brownfield facilities to meet modern AM standards (Lins & Oliveira, 2020). To successfully implement this strategy in HMLV environments, contemporary setups must transition toward dynamic RMS that allow legacy assets to adapt to varying product structures.

However, while the macro-level digital transformation of factory-wide networks is widely documented in contemporary literature, a critical research gap persists in scaling these advanced frameworks down to the localized workstation and individual robot cell level within the SME sector. In HMLV production environments, manufacturing resilience is fundamentally determined not by sweeping enterprise-wide software overhauls, but by the rapid, flexible reconfigurability of the immediate physical workplace. Therefore, narrowing the operational and technical scope specifically to integrated collaborative robot cells, smart modular fixtures, and adaptive end-effectors represents a vital application area. By focusing the architectural interventions directly at the machine and tool interface, resource-constrained enterprises can achieve targeted agility, turning standalone legacy equipment into a versatile asset capable of independent product-driven adjustments without requiring massive capital reinvestments.

A critical enabler for these advanced systems is seamless interoperability and decentralized data architectures. Modern trends favour open-source standards and universal communication protocols, such as Open Platform Communication Unified Architecture (OPC UA) or Message Queuing Telemetry Transport (MQTT), that dismantle traditional data silos. These two protocols address complementary aspects of the same problem. OPC UA (IEC 62541) contributes a semantic information model rather than a raw data stream: each transmitted value carries its meaning, unit and source, allowing heterogeneous equipment to be described in a single machine-readable structure that can serve directly as a foundation for Digital Twin models, while platform independence and built-in authentication and encryption make it applicable across both legacy and modern edge controllers. In contrast, MQTT (ISO/IEC 20922) is a lightweight publish/subscribe transport in which devices publish measurements to topics on a central broker and consuming systems subscribe to them, decoupling senders from receivers and allowing a single broker to serve a large number of sensing points. Its minimal resource footprint permits operation on controllers with very limited computing capacity and over bandwidth-constrained or intermittent connections, which are precisely the conditions encountered when retrofitting legacy equipment. According to Lu, the ability to create a transparent data flow across heterogeneous equipment landscapes is essential for the resilience required in Industry 5.0 (Lu, 2017). For SMEs, this means the capacity to rapidly integrate new sensing technologies into existing

robotic cells, ensuring that data-driven decision-making is based on high-fidelity, real-time information. By vertically integrating this shop-floor data with enterprise layers according to standards such as ISA-95, low-level machine signals can be continuously aggregated into real-time metrics, such as operation cycle time and Overall Equipment Effectiveness (OEE), providing the empirical triggers necessary for bottleneck identification and subsequent system adjustments.

Furthermore, the role of DT has evolved from simple monitoring tools into complex, predictive environments for Human-Robot Collaboration. In an Industry 5.0 framework, DTs are utilized to synchronize physical robotic movements with virtual safety zones and optimized workflows. This closer time-and-space sharing between humans and machinery demands a rigorous adherence to updated safety regulations, specifically the newly harmonized ISO 10218:2023 series, which governs power and force-limiting collaborative operations. Liu and Lu et al. argue that DT-driven manufacturing allows for the virtual validation of reconfigurations, which is vital for HMLV production (Lu et al., 2020). This capability ensures that SMEs can remain agile and resilient in the face of fluctuating market demands and supply chain disruptions.

Finally, the democratization of Artificial Intelligence (AI) through visual programming and perception-based interfaces is a key trend in Advanced Manufacturing. Instead of requiring deep expertise in complex syntax-based coding, shop-floor operators can now leverage AI-enhanced vision and adaptive control systems through intuitive graphical environments. Wang et al. emphasize that AI-driven perception allows robotic cells to handle the variability inherent in SME production. By simplifying the interaction between humans and advanced machines through visual programming frameworks, these developments directly support the Industry 5.0 vision of a resilient and inclusive industrial workforce (Wang et al., 2018). This shift ensures that high-level automation remains a versatile tool that can be rapidly reconfigured by the existing workforce to meet shifting production needs.

1.3 Objectives and Research Questions

The main goal of this thesis is to develop a comprehensive design methodology for transforming legacy robotic cells into I5.0-ready Advanced Manufacturing (AM) systems, enabling SMEs to enhance manufacturing efficiency and flexibility through smart sensor integration, real-time data analytics, and digital twin frameworks. The research employs a knowledge-driven design methodology combined with experimental retrofitting, where existing robotic units are transformed into adaptive CPS. This approach creates a technological synergy between Industrial Internet of Things (IIoT) as connectivity, MV as machine perception, and DT environments as simulation and prediction, establishing a data flow that allows for rapid reconfiguration and optimized decision-making, specifically tailored for the high-mix low-volume production environments typical of SMEs.

Based on the main goal of this research and the identified research gaps, the following research questions are formulated:

- **RQ1:** Which digital and physical retrofitting features provide the highest value-add when transforming legacy robotic cells into Industry 5.0-ready systems?

- **RQ2:** What is the impact of integrated data analytics on process transparency in brownfield environments, and how can these real-time metrics dynamically trigger reconfiguration?
- **RQ3:** How does the proposed design methodology (integrating PEM and Digital Twin) facilitate the rapid reconfiguration of workstations into flexible automated units?
- **RQ4:** Which functional design elements ensure system interoperability and safety in Human-Robot Collaboration, and how is their impact validated through CPS metrics?

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

- **Task 1 - Establish a modular CPS architecture** specifically tailored for the technical limitations of legacy robotic systems**.**
- **Task 2 - Implement a real-time data collection framework** to enhance transparency and provide feedback loops within brownfield SME environments.
- **Task 3 - Develop a systematic reconfiguration methodology** using a PEM, synchronized with Digital Twin virtual validation, to map product features against robotic capabilities.
- **Task 4** - **Implement vision-based quality control logic and modular programming** to enable system autonomy and safe Human-Robot Collaboration.
- **Task 5 - Validate the system's performance** via experimental use-cases, evaluating the impact on throughput, cycle times, and OEE.

The visualization between the RQs and the defined research tasks are summarized in Table 1. The proposed tasks are created for ensuring conceptual and practical layers of this research. Primary RQ indicates the core focus of the respective research task, while the cross-markers map the overall contribution across all relevant research questions.

Table 1. Mapping of RQ-s and research tasks.

Research Question	Primary Tasks	Supporting Tasks	Publication
RQ 1: Which retrofitting feature provides highest value?	**Task 1**	Task 3, Task 5	I, II
RQ 2: What is the impact of data analytics and how real-time metrics trigger reconfiguration?	**Task 2**	Task 4, Task 5	I, II, IV
RQ 3: How does the proposed methodology facilitate the rapid reconfiguration of workstations into flexible automated units?	**Task 3**	Task 4, Task 5	III, IV, V, VI
RQ 4: Which functional design elements ensure system interoperability and safety in Human-Robot Collaboration, and how is their impact validated through CPS metrics?	**Task 5**	Task 2, Task 4	III, IV, VI

By organizing the research around these objectives, questions and tasks, the thesis provides a systematic approach for developing and evaluating reconfiguration methodology for integrated robotic systems.

1.4 Contribution of the Thesis and Dissemination

The contribution of this dissertation is divided into three main pillars: scientific methodology, industrial validation, and educational integration.

1. **Scientific Contribution & Methodology:**

- Reconfiguration Decision Framework: Developing a systematic decision-making framework based on the Product Evaluation Matrix (PEM) to evaluate product families and operational parameters for workstation reconfigurability in High-Mix Low-Volume (HMLV) manufacturing.
- Cyber-Physical Retrofitting Architecture (3C): Formulating a multi-layer retrofitting model structured around Computation, Communication, and Control. This formalizes non-invasive signal capture, operational state validation logic, and vertical data transmission between legacy shop-floor assets and management software.
- Integrated Quality Control Workflow (CBQC): Formulating the functional coupling between machine vision inspection and collaborative robotics for quality control, defining how automated inspection pass/fail signals control robotic handling and part sorting.
- Simulation-Guided Layout Evaluation: Integrating empirical cycle-time data with Discrete Event Simulation (DES) to evaluate workstation layout modifications and dynamic bottlenecks before physical cell reconfiguration.

2. **Industrial Novelty & Experimental Validation:**

- Cycle-Time Decomposition and Bottleneck Analysis: Applying cycle decomposition to live production data to locate operational delays and validate throughput improvements after cell reconfiguration.
- Modular Workpiece Fixturing: Designing and validating modular fixtures utilizing additive manufacturing inserts and multi-position clamping to reduce changeover times between product variants.
- Automated Inspection Workstation: Implementing and testing an automated inspection cell in an electronics manufacturing environment, confirming proof of concept in part sorting based on optical inspection criteria.

3. **Educational Novelty & Human-Centric Integration:**

- Learning Factory Testbed: Implementing practical demonstration and testing cells at the TTK UAS Demonstration Centre to teach CPPS retrofitting and robotic integration methods to students and industry engineers.
- Operator-Oriented System Interaction: Structuring collaborative robot programming and station HMIs into intuitive, modular tasks to lower programming barriers and reduce operational complexity for shop-floor personnel.

The methodological foundations and technical implementations supporting these contributions are elaborated in Chapters 3 and 4, which detail the cyber-physical system

architecture, communication protocols, reconfiguration methodology, and the automated inspection cell.

The practical realization and experimental validation are documented across Publications I–VI:

- Publications I and II establish the cyber-physical retrofitting architecture and evaluate integration requirements for brownfield SME environments.
- Publications II and IV focus on non-invasive data acquisition, signal validation logic, and real-time production monitoring.
- Publications III, IV, V and VI formulate the reconfiguration decision framework and simulation-guided workstation layout evaluation.
- Publications III and VI validate the integration of machine vision and collaborative robotics for automated quality inspection.
- Publication V establishes the educational Learning Factory testbed for human-centric integration and methodology validation.

A comparative summary of the contributions across the three pillars is synthesized in Table 2.

Table 2. The summary of scientific, industrial and educational novelties.

Contribution Pillar	**Methodological Scope**	**Practical Realization**	**Practical Outcome**
Scientific Contribution & Methodology	Product Evaluation Matrix evaluation method, 3C cyber physical retrofitting model, Machine vision-to-robot control logic, Simulation-based layout assessment.	Systematic workstation evaluation, Formal signal validation logic, Virtual cell modelling.	Structured planning method replacing empirical trial-and-error in cell reconfiguration.
Industrial Novelty & Experimental Validation	Cycle-time decomposition and simulation in digital twin environment	Dimusa hardware installation on legacy machinery, Industrial vision inspection workstation, Modular fixtures for rapid reconfiguration	Measurable throughput improvement, bottleneck reduction, automated defect containment.
Educational Novelty & Human-Centric Integration	Human-centric I5.0 concepts for SMEs, Task-oriented programming structures for HRC.	Educational Learning Factory testbed, Operator-focused HMI dashboards.	Practical engineering upskilling in reconfiguration.

Together, these scientific, industrial, and educational contributions establish a coherent framework that bridges theoretical modelling with practical shop-floor application. By synthesizing non-invasive monitoring, modular tooling, and accessible

operator interfaces, this dissertation provides a validated, scalable roadmap for the cyber-physical transformation of brownfield manufacturing environments.

Dissemination of the Results and Publications

The research was carried out from 2020 to 2025 at TalTech University, TTK University of Applied Sciences and over a three-month period in 2023 at the Faculty of Industrial Computing and Robotics of Valencia Polytechnic University. The results of the PhD thesis have been presented at four international conferences. Four articles are published in Journals (International Journal of Engineering and Technology, Journal of Machine Engineering and Proceedings of the Estonian Academy of Sciences) and the rest in the proceedings of conferences: Proceedings of the ASME (American Society of Mechanical Engineers), Proceedings of Estonian Academy of Science and AIP Conference Proceedings.

1.5 Structure of the Dissertation

The research presented in this thesis is organized into five interrelated chapters that follow a logical progression from initial conceptualization and theoretical framing to experimental validation and final synthesis. Following this introductory chapter, which establishes the research background, identified gaps, and primary objectives, Chapter 2 provides a comprehensive state-of-the-art analysis. This review focuses on the evolution of Industry 4.0 and 5.0, specifically examining the technological and operational challenges inherent in brownfield integration and reconfigurability within SME-scale production while establishing the academic boundaries for RMS, Key Performance Indicator (KPI) hierarchies and the harmonized ISO 10218:2023 safety regulations.

The core scientific and methodological contribution of the work is developed in Chapter 3, where a structured, reconfiguration methodology for the design and performance analysis of robotic cells is proposed, as detailed in Publications IV and VI. This chapter formalizes the decision logic of the PEM, introduces the low-cost modular architecture for retrofitting legacy cells, and defines the data-driven trigger structures for system adjustments.

Building upon these methodological foundations, Chapter 4 explores the practical implementation and experimental results of the proposed framework. This includes an in-depth analysis of industrial data flows, integration of machine vision features, and the modernization of legacy manufacturing units as documented in Publications I, II, and III, focusing specifically on the deployment of a CBQC system utilizing adaptive end-effectors, smart fixtures and comprehensive performance analysis via throughput and OEE.

Finally, the thesis concludes with Chapter 5, which summarizes the primary research outcomes, provides direct answers to the research questions, and outlines strategic directions for future inquiry in the field of retrofitting and human-centric manufacturing systems. The graphical overview of the thesis structure is illustrated in the Figure 2.

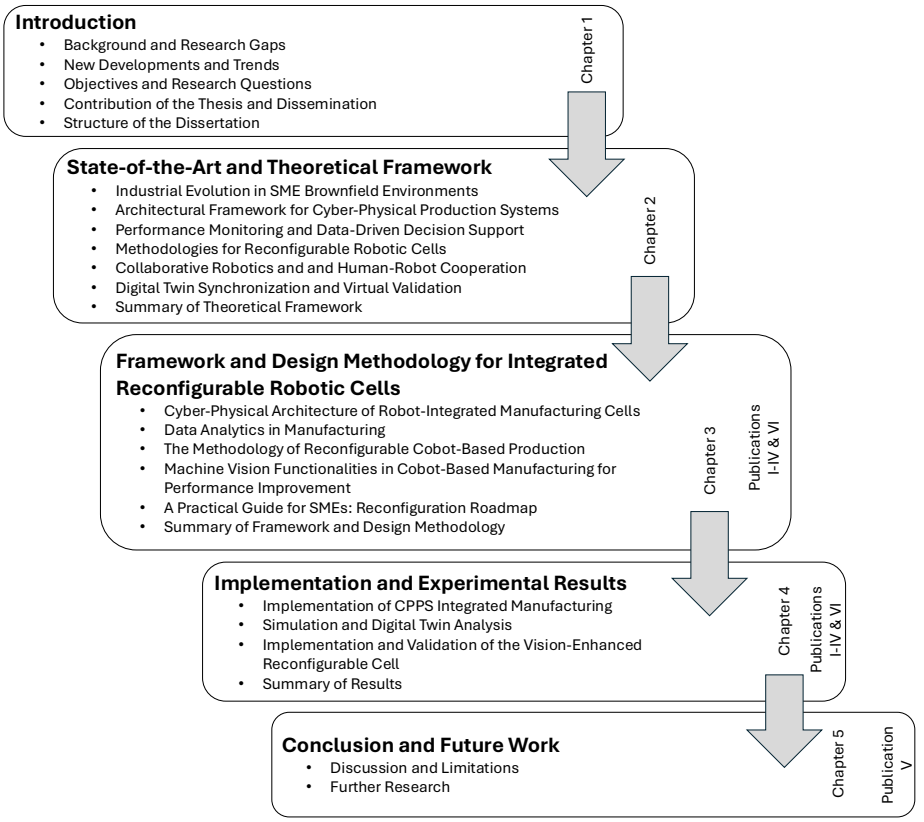


Figure 2. Structure of the doctoral thesis

Beyond the main chapters, the dissertation is supported by a comprehensive list of publications, a detailed statement of the author's contributions, and an Estonian-language summary to ensure the results are accessible to both the local industrial community and the international research field. The chosen structure is designed to follow a logical, industrial narrative: it starts by diagnosing the constraints of legacy systems, advances through the systematic development of reconfigurable methodologies, and concludes with their validated impact. Ultimately, this organization maintains the necessary conceptual rigor while ensuring the results remain grounded in practical relevance, offering a transparent view of how each research objective has been systematically addressed.

2 State-of-the-Art and Theoretical Framework

This chapter reviews the state of the art and establishes the theoretical framework for this dissertation. Instead of treating automation in isolation, it focuses on integrating legacy shop-floor machinery with modern digital control and data architectures. To support the proposed design and reconfiguration methodology, this review is structured around six core areas:

1. Industrial Evolution in SME Brownfield Environments: Analysing the distinct boundaries of brownfield development and legacy hardware while detailing the operational imperatives required to foster manufacturing resilience under the human-centric Industry 5.0 paradigm. This foundation provides the baseline knowledge-driven design inputs needed to navigate real-world resource constraints within HMLV production cycles.
2. Architectural Framework for CPPSs: Evaluating vertical and horizontal integration strategies via the standard ISA-95 hierarchy alongside the structural mechanics of the 3C architecture to ensure seamless data interoperability and cloud-readiness.
3. Performance Monitoring and Data-Driven Decision Support: Scrutinizing advanced manufacturing analytics and outlining how shop-floor metrics – principally operation cycle time and the OEE framework – serve as the vital empirical diagnostic tools for bottleneck identification.
4. Methodologies for Reconfigurable Robotic Cells: Investigating the core principles of RMS, focusing on structural hardware modularity and leveraging the PEM as a deterministic decision-support mechanism for transforming rigid or manual workstations into agile layouts.
5. Collaborative Robotics and HRC: Mapping the operational landscape of human-machine interactive cells and task allocation while aligning system deployments with the newly harmonized industrial safety regulations, specifically the ISO 10218:2023 series and associated force-verification specifications.
6. Digital Twin Synchronization and Virtual Validation: Addressing the bidirectional real-time data exchange mechanisms required to power Discrete Event Simulation (DES) models as predictive advisory tools, combined with the deployment of machine vision and rule-based perception features for autonomous quality control application.

Collectively, these systematic evaluations construct the indispensable scientific boundaries and validation paradigms into which the integrated reconfigurable methodology proposed in Chapter 3 and empirically documented in Chapter 4 must fit.

2.1 Industrial Evolution in SME Brownfield Environments

Modern manufacturing systems have evolved into complex socio-technical ecosystems that integrate advanced physical processes with pervasive digital intelligence (Monostori et al., 2016). This evolution is characterized by a transition from the rigid economies of scale typical of traditional mass production toward flexible, smart factories capable of handling HMLV production cycles (Koren, 2010; Matt et al., 2020). As the global industrial landscape moves toward the Industry 5.0 paradigm, the focus has shifted from mere efficiency to a more holistic approach encompassing human-centricity, sustainability, and industrial resilience (European Commission, 2020).

2.1.1 Defining the Brownfield Reality and Legacy Systems

For the majority of SMEs, which constitute 99.8% of all EU businesses, the path to digitalization contrasts sharply with greenfield development, where production lines and data architectures are designed from scratch without legacy constraints. Building on the operational definition established in Section 1.1, the brownfield reality in manufacturing primarily entails retrofitting existing infrastructure with IoT capabilities – a far more economically viable and pragmatic choice for SMEs than capital-intensive new factory replacements (Etz et al., 2020; Tran et al., 2022).

In the scope of this research, legacy robotic systems are defined as industrial manipulators that are technologically functional and robust but lack modern data connectivity and the ability to communicate with cloud-based platforms. Guerreiro and Lins (Guerreiro et al., 2017) emphasize that while retrofitting such systems is economically viable, there is a distinct lack of standardized frameworks for integrating legacy sensors with modern analytics. Consequently, cyber-physical retrofitting has emerged as a cornerstone of sustainable industrial evolution, enabling legacy assets to meet modern standards (Lins & Oliveira, 2020).

2.1.2 Transitioning to Industry 5.0 and SME Resilience

While Industry 4.0 focused heavily on automation and Machine-to-Machine (M2M) communication, Industry 5.0 reintroduces the human element into the production loop, operating under a strict human-centric priority (Tran et al., 2022). This paradigm shift is particularly critical for SMEs facing unprecedented labour shortages and demographic challenges, where digital transformation is a necessity for survival and industrial resilience (Eurofound & Cedefop, 2020).

Resilience in this context refers to the system's ability to remain agile and adaptive in the face of fluctuating market demands. This requires a move away from rigid, standalone automation toward CPS where computational algorithms and physical processes are networked and operate in synchrony. By upgrading existing production cells to the level of intelligence required by modern standards, SMEs can leverage their Brownfield assets to achieve the flexibility needed for high-variation product environments.

2.1.3 Knowledge-Based Design Inputs for SME Robotic Systems

To bridge the gap between legacy hardware and modern intelligence, the process of designing these integrated systems – referred to as Manufacturing System Design — requires a precise synthesis of diverse parameters (Vaughn et al., 2002). In a Knowledge-Based Engineering (KBE) framework, robotic cells are conceptualized as a hierarchical architecture comprising system, sub-system, and machine levels (Benkamoun et al., 2014). For SMEs operating in Brownfield environments, the transition between these levels is bounded by specific constraints, requiring a knowledge-driven approach to system design.

Research indicates that the most significant factors influencing MSD are not always direct technical specifications, but broader operational parameters. Key design inputs for these SME environments include:

- **Market Need and Product Volume:** Fluctuations in product demand directly impact capacity needs and shape physical design decisions, such as machine selection and layout planning (Koren, 2010).

- **Product Mix:** A high degree of product variety necessitates a trade-off in production volume per part, requiring a highly reconfigurable approach.
- **Existing Resource Constraints:** The boundary conditions are heavily set by existing legacy technologies and financial limitations (e.g., rapid payback periods and implementation costs) typical of SME environments (Zhong et al., 2017).

Ultimately, these crucial factors must be analysed as primary design inputs to ensure that the fundamental manufacturing system architecture aligns with the specific strategic needs of the enterprise while maximizing the utility of existing assets.

2.2 Architectural Framework for Cyber-Physical Production Systems

The efficacy of modern reconfigurable manufacturing relies heavily on the underlying communication infrastructure and system architecture. To achieve the level of integration required for flexible SME environments, the physical world – comprising legacy industrial machinery, actuators, and sensors – must be systematically interfaced with an information network that enables the continuous transmission of data to the digital realm (Collin & Saarelainen, 2016).

2.2.1 Vertical and Horizontal Integration – ISA-95 Standard

In a modern manufacturing ecosystem, data must flow seamlessly from the shop floor up to the enterprise level. This vertical integration is fundamentally structured around the ISA-95 standard, which defines the hierarchical levels of manufacturing operations and facilitates the synchronization of Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) (Scholten & Brandl, 2022).

For SME brownfield environments, achieving this vertical integration means establishing a reliable data flow from legacy field-level devices, such as simple sensors and Programmable Logic Controller (PLC), up to the business planning level. As illustrated in Figure 3, the ISA-95 model provides the structural blueprint for this integration, defining the specific timeframes and network types required for each operational layer.

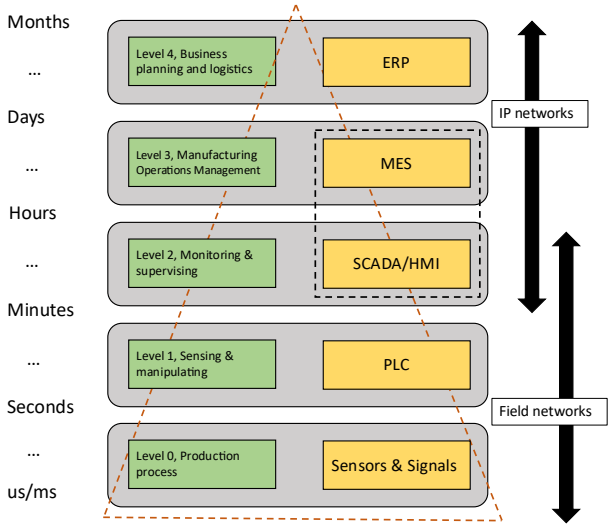


Figure 3. Integration and connectivity according to ISA-95 (Lydon, 2020)

By utilizing this hierarchical connectivity, physical systems are integrated into a larger hyper-physical ecosystem, enabling companies to develop novel operating models and more autonomous, dynamic solutions.

Furthermore, within the European industrial and regulatory landscape, this functional hierarchy is adopted and applied as the equivalent international standard IEC 62264-1:2013 (Enterprise-Control System Integration). This alignment ensures that the architectural models and data exchange protocols defined by ISA-95 are fully harmonized with European manufacturing frameworks, thereby enabling standardized vertical integration across global supply chains.

2.2.2 The 3C Architecture of Cyber-Physical Systems

This digital integration is embodied in the concept of CPS. CPS represent a paradigm shift in engineering, defined as integrated systems where computational elements – the cyber domain – are tightly coupled with physical processes through sensing, communication, and actuation mechanisms (Lee, 2008). Transcending traditional embedded systems, CPS enable real-time interaction between digital computation and physical components, facilitating responsive and intelligent behaviour in complex environments (Melicher et al., 2019).

The structural integrity of a CPS is built upon three interdependent layers (Liu et al., 2017):

1. **The physical layer:** Consisting of sensors and actuators that perceive and manipulate the physical world.
2. **The communication layer:** Ensuring that data is transmitted reliably and with bounded latency to support real-time requirements.
3. **The computation and control layer:** Processing the incoming data, executing complex control algorithms, and implementing strategic decision-making.

The interaction and specific vulnerabilities between these layers are visualized in Figure 4, demonstrating the core 3C architecture required for a functional CPS.

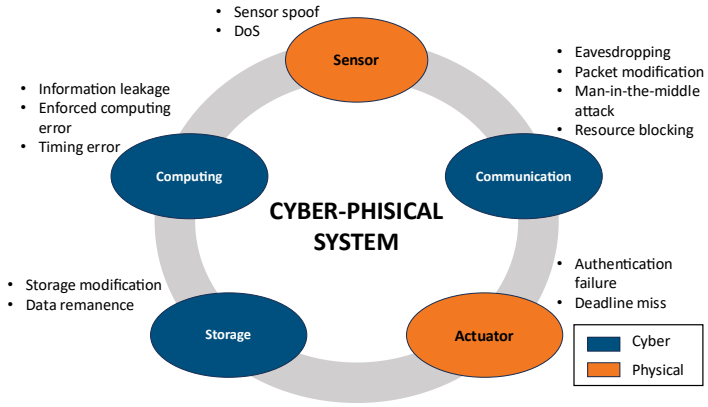


Figure 4. The 3C Layers of CPS (Onik et al., 2019)

Within this doctoral dissertation, the 3C architecture for CPS serves as a core structural pillar to systematically bridge the gap between heterogeneous physical legacy infrastructure and cognitive digital control layers. While the current section delineates the overarching theoretical boundaries and standard concepts of this model, its specific adaptation to SME brownfield environments, and detailed modular system schematics are developed and in Section 3.2. The direct integration of this theoretical 3C framework

with the reconfigurability methodologies advanced in the subsequent chapters ensures a seamless transition from a conceptual blueprint into a data-driven, shop-floor application.

2.2.3 Cyber-Physical Production Systems and Interoperability in SMEs

When this CPS framework is applied specifically to the manufacturing domain, it evolves into Cyber-Physical Production Systems. Unlike general-purpose systems, CPPS are characterized by their ability to facilitate M2M communication and autonomous coordination across the shop floor (Monostori et al., 2016).

In a CPPS environment, individual smart units are networked together to form a collective, self-organizing intelligence that can respond dynamically to fluctuations in product mix and volume (Mahmood et al., 2019). To achieve this level of integration in legacy environments, robust open-source protocols such as OPC UA and MQTT are utilized to ensure interoperability between different hardware components (Microsoft, 2022). This continuous one-way data ingestion – where every physical action is mirrored in the digital realm – serves as the fundamental precondition for real-time performance monitoring and the development of predictive advisory simulation models.

In the context of this dissertation, this paradigm transitions from a macro-level theoretical taxonomy into a localized engineering blueprint tailored for SME brownfield environments. The reconfigurable robotic cell developed in this research acts as a functioning embodiment of a bounded CPPS, where the physical domain – consisting of legacy industrial manipulators, collaborative robots, and smart auxiliary fixtures – is dynamically coupled with an advanced digital cyber layer. By closing the feedback loop between physical operations and computational decision-making, this thesis demonstrates how these cyber-physical characteristics can be scaled down to individual workstations to enable cost-effective flexibility and autonomous responsiveness. The underlying logic of this localized framework is structured in Chapter 3 and empirically validated through the industrial use-cases presented in Chapter 4.

2.3 Performance Monitoring and Data-Driven Decision Support

With the cyber-physical architecture established, the next critical step for SME brownfield environments is translating the harvested raw data into actionable intelligence. Advanced Analytics has become vital for making optimal decisions in modern manufacturing, enabling companies to capitalize on short-, medium-, and long-term activities by automating decision support rather than relying on manual calculations (Monostori et al., 2016).

2.3.1 Advanced Analytics in Manufacturing

The application of Data Analytics requires a sufficient and structured database. By combining existing information gathered from MES and ERP databases with external factors, it is possible to use advanced analytics to extend the simulation model and predict future trends. The analytical models applied in manufacturing can be divided into three primary computerized data processing methods (Menezes et al., 2019):

1. **Descriptive analytics:** The accounting and analysis of historical data, used in backcasting practices and forecasting seasonal demands.
2. **Predictive analytics:** Considers near-past data to predict future trends, tendencies, and behaviours through causation and correlation models.

3. **Prescriptive analytics:** Finds or prescribes the optimal mode, route, or operational moves based on the input data and predictive models.

In practice, the data analysis process is cyclical and consists of standardized steps: business understanding, data understanding, data preparation, modelling – such as correlation and regression, evaluation, and deployment (Chapman et al., 1999; Chapman et al., 2000; Groggert et al., 2018). Within the context of reconfigurable robotic cells, predictive and prescriptive analytics are essential for executing "what-if" scenarios in Digital Twin environments before applying physical changes.

2.3.2 Key Performance Indicators and OEE Framework

Key Performance Indicators must be systematically established as a foundational requirement for operationalizing manufacturing data analytics. A KPI should be considered a company's vital sign, describing the actual situation and the degree of goal fulfilment. Using KPIs as a diagnostic tool provides an opportunity to identify bottlenecks in production, increase equipment effectiveness, and monitor the progress of production orders (Kangru, Mahmood, et al., 2020).

Today, KPI monitoring is a multi-level, real-time process which begins at the shop floor and reaches the company's strategic level. The selection of KPIs is generally a Multi-Criterion Decision-Making problem, and the choice must be as problem-oriented as possible (Kaganski et al., 2017; Kibira et al., 2018). For SME production units, these indicators are hierarchically linked across three organizational levels, as mapped in Table 3.

Table 3. Key Performance Indicator Hierarchy (Kangru, Mahmood, et al., 2020)

Level	Performance Indicators	
I Strategic	Utilization Overall Equipment Effectiveness	Throughput Discounted Payback Period
II Tactical	Availability Performance Quality Planned Production Time	Actual Production Time Set-up Time vs Cycle Time Operating time/Idle Time vs Cycle Time
III Shop-Floor	Total Products Produced Finished Products Activity Processing Time	Operating Time Ideal Processing Time Total Run Time

At the shop-floor level (Level III), physical inputs are measured directly from the workstation or machine. For robotic cells, the primary performance metric is the operation cycle time (T_{cycle}). This metric aggregate active processing time, robot movement time, and critically, non-value-added durations such as idle waiting time (T_{idle}) and system adjustment/setup time (T_{setup}).

These lower-level metrics feed into the tactical and strategic levels (Levels II and I) to calculate the OEE, which measures availability, performance, and quality. In high-mix environments, frequent changeovers significantly impact productivity (Snatkin et al., 2013). Therefore, real-time deviations in these specific KPIs, such as an excessive T_{idle}

indicating a structural bottleneck, serve as the fundamental, empirical triggers that initiate the rapid reconfiguration logic detailed in the subsequent chapters.

2.4 Methodologies for Reconfigurable Robotic Cells

As the industrial product volume and technical solutions continuously evolve, manufacturing enterprises – particularly SMEs – are required to upgrade their production systems to remain competitive. Modern manufacturing industries are transitioning rapidly towards HMLV production. To realize customer-centric manufacturing, production systems must support a "batch size 1" operational model, which demands a significant increase in manufacturing flexibility. Unlike traditional flexible systems, the RMS is designed for rapid changes in structure, both in hardware and software, to adjust production capacity and functionality within a specific part-family. The core advantage of the RMS lies in its evolvability, multi-functionality, and survivability in high-mix environments (Koren, 2010; Koren et al., 2018). However, existing RMS frameworks are often too complex or capital-intensive for small enterprises to implement directly. Therefore, a dedicated reconfiguration methodology must be designed to meet the technical requirements and resource constraints of SMEs operating in brownfield environments.

2.4.1 Modularity and System Architecture

The successful implementation of a reconfigurable robotic cell depends on its modularity. Modularity allows the system to be decomposed into independent units that can be interchanged or upgraded. Building on the research of Yim and Duff (Yim et al., 2000), this methodology distinguishes between three primary subtypes of modularity in system design:

1. **Slot Architecture:** Each interface between components is of a different type; therefore, various components cannot be interchanged. An example is a robot arm with rigid links and specific motor/sensor interfaces.
2. **Bus Architecture:** Physical components connect via a common, standardized interface. Similarly to a laptop with USB ports, this allows modular elements to be added or reconfigured within the system.
3. **Sectional Architecture:** All interfaces are of the same type, and there is no single base component to which all others attach.

In the context of this research, the principles of slot and bus architecture are utilized to enable the reconfiguration of legacy robot cells into integrated quality control systems.

2.4.2 The Product Evaluation Matrix as a Decision Tool

A critical research gap in RMS implementation is the logic used to map physical product features directly to robotic capabilities. To address this, the proposed methodology utilizes the Product Evaluation Matrix, originally presented by Paramasivam and Senthil (Paramasivam & Senthil, 2009).

The PEM serves as a systematic design tool to analyse which product features (e.g., size, shape, weight, assembly type) have the most significant impact on system requirements. In this thesis, the PEM is utilized as the primary logic for Task 3, providing the empirical basis for rapid reconfiguration as sought in RQ3. By mapping these features against system effects—such as the need for specialized gripping or multi-angle vision

inspection – the PEM empowers the human decision-maker to prioritize parameters for a specific manufacturing context.

2.4.3 Transitioning from Manual to Collaborative Workstations

The reconfiguration process often involves the conversion of manual or static workstations into collaborative environments. This transition requires a multi-criteria evaluation of production indexes, including technical feasibility, safety, and economic aspects (Gualtieri et al., 2019).

Building on the work of Kangru (Kangru, Riives, et al., 2020) and Heydaryan (Heydaryan et al., 2018) , the methodology emphasizes a hierarchical decision-making process where productivity and human safety are evaluated concurrently. As established in Publication VI, this structured approach ensures that the human operator remains central to the system, while the robotic unit is reconfigured to handle repetitive or high-precision tasks, such as CBQC.

2.5 Collaborative Robotics and Human-Robot Cooperation

Integrating reconfigurable robotic systems into SME brownfield environments requires close interaction between human operators and automated equipment. This section establishes the operational and regulatory framework for HRC. To optimize cell efficiency and flexibility, systematic human-robot task allocation methodologies must be evaluated. Furthermore, because reconfigurable systems introduce variable cellular layouts and changing operational hazards, strict compliance with updated industrial safety regulations and standards is mandatory. This review defines the safety and operational constraints required for the design methodology developed in Chapter 3 and the physical validation cases presented in Chapter 4.

2.5.1 The Regulatory Landscape and Safety Standards

Safety is the most critical factor in any project involving human-robot interaction. Historically, the safety requirements for collaborative systems were governed by the foundational ISO 10218-1 and ISO 10218-2 standards, supplemented by the technical specification ISO/TS 15066:2016. However, the field has recently transitioned toward the updated ISO 10218:2023 series, which now integrates the collaborative requirements – previously found in separate technical specifications – directly into the main industrial robot standards.

This update is significant for SME brownfield environments, as it provides a more unified framework for power and force limiting and speed and separation monitoring. Furthermore, the validation of these collaborative cells is now supported by specific frameworks such as ISO/PAS 5672:2023, which provides standardized methods for measuring force and pressure in HRC scenarios, and ISO/TR 20218-1:2018, which focuses specifically on the safety of end-effectors and grippers in collaborative environments. In this framework, the robot is not merely a tool but a partner that must operate within these safety-rated monitored limits to ensure the physical well-being of the human operator.

2.5.2 Human-Robot Activity Allocation and Cooperation Levels

The transition to a collaborative environment requires a systematic approach to task distribution. The Human-Robot Activity Allocation procedure is a fundamental part of the conversion process from manual to automated systems. Starting from an existing manual workstation, this procedure allows for the separation of tasks and activities between operators and robots by considering production indexes such as technical feasibility, safety, ergonomics, and economic aspects (Gualtieri et al., 2019).

The integration of collaborative robots can be characterized by the specific level of cooperation (El Zaatari et al., 2019):

- Sequential Cooperation: The robot and human work on the same part at different times.
- Simultaneous Collaboration: Both agents work on the same task at the same time in a shared workspace.
- Supportive Cooperation: The robot monitors human movements and contributes as needed to the process.

To ensure successful integration, SME management must implement structured training programs and subsequent performance analysis. The model proposed by Oberc (Oberc et al., 2019), illustrated in Figure 14, serves as a guideline for this human-centric training cycle, ensuring that the existing workforce can effectively manage and reconfigure the robotic cell.

2.5.3 Adaptive End-Effectors and Sensory Systems

The versatility of a collaborative cell in a high-mix environment is largely determined by its end-effector or tool. SME production typically requires adaptive gripper systems capable of handling parts with various shapes and delicate components without necessitating a full tool change. Kinematically, these systems often utilize parallel or radial gripping, with modern reconfigurable grippers allowing for the adjustment of finger count, range, and geometry (Birglen & Schlicht, 2018).

For adaptive systems, the integration of force, torque, and position sensing is essential for secure grasp control and condition monitoring. As established by Birglen (Birglen, 2019) and Zhang (Zhang et al., 2021), these sensory functions allow the robot to handle flexible and delicate components – such as the IoT modules discussed in this thesis – with high reliability. This physical perception, when synchronized with machine vision, forms the foundation for the rule-based decision-support logic required for rapid system reconfiguration.

2.6 Digital Twin Synchronization and Virtual Validation

The final stage of establishing a reconfigurable robotic cell involves creating a data-driven link between the physical shop floor and a virtual environment. To achieve effective predictive mapping between physical shop-floor equipment and virtual cells, this review integrates the foundational DT reference model developed by Lu and Liu (Lu et al., 2020). Their framework outlines the necessary layers for real-time data-driven synchronization, which enables the alignment of DES with perception-based inspection features. Within the scope of this dissertation, this reference architecture is utilized to design the predictive validation and automated quality control layers for reconfigurable robotic cells. This theoretical baseline defines the operational constraints for the engineering methodology structured in Chapter 3 and the physical use-cases validated in Chapter 4.

2.6.1 Digital Twin as a Predictive Advisory Tool

A Digital Twin is defined as a real-time virtual representation of a physical object or system, offering immense potential for process optimization and simulation. In modern manufacturing, the role of DT has evolved from simple monitoring to a complex environment for HRC and virtual validation of reconfigurations (Tao et al., 2018).

As highlighted by Tao, the primary technological bottleneck remains the bidirectional data exchange and real-time synchronization between legacy devices and digital models. For SMEs, establishing this link is crucial for minimizing downtime by validating new workflows in a virtual environment before physical implementation – a process known as Virtual Validation. In this research, DES tools (Babulak & Wang, 2010) are utilized to perform "what-if" analyses, balancing efficiency gains against system stability.

2.6.2 Machine Vision and Perception-Based Features

To allow a reconfigurable cell to handle production uncertainties, it must be equipped with sensory perception, primarily Machine Vision. MV systems are used for a broad range of applications, including identification, positioning, and defect detection, offering significantly increased throughput compared to manual inspection (Huang et al., 2018).

Furthermore, the democratization of Machine Learning (ML) allows these systems to automatically learn patterns from data, facilitating autonomous defect classification and performance optimization (Razvi et al.). In the context of this thesis, MV acts as the vision system of the robotic cell, providing the real-time feedback required for the rule-based decision logic to decide between "OK" and "NOK" product paths.

2.7 Summary of Theoretical Framework

This chapter synthesized the state-of-the-art literature and theoretical frameworks required to develop reconfigurable and integrated robotic systems for SME brownfield environments. The review systematically evaluated the core architectural and technical domains necessary to enable flexible manufacturing:

- Cyber-Physical Production Systems: Examining vertical integration through ISA-95/IEC 62264-1:2013 standards and data-driven mapping via the 3C architecture.
- Performance Monitoring and RMS: Analysing operation cycle time and OEE as diagnostic tools and evaluating RMS principles to support a "batch size 1" operational model.
- Human-Robot Collaboration and Virtual Validation: Defining task allocation structures under strict compliance with ISO 10218:2023 safety regulations, alongside DT architectures based on the Lu and Liu (2020) reference model for discrete event simulation and perception-based inspection.

Establishing these theoretical boundaries is a mandatory condition for resolving the hardware and software integration bottlenecks typical of resource-constrained manufacturing facilities. Synthesizing these distinct engineering domains provides a standardized technical baseline that justifies the design inputs and boundary constraints utilized in this study. Consequently, this comprehensive framework directly enables the formulation of the design methodology presented in Chapter 3 and defines the experimental validation parameters for the empirical industrial use-cases documented in Chapter 4.

3 Framework and Design Methodology for Integrated Reconfigurable Robotic Cells

This chapter presents the development of a design methodology and implementation of CPS applications for robot-integrated manufacturing cells, specifically tailored for SME environments with HMLV production cycles. This transition necessitates production systems that can be rapidly reconfigured to accommodate new product variants without extensive downtimes or prohibitive investment costs. The proposed methodology moves beyond conventional automation by introducing modular, data-driven framework where physical hardware and digital intelligence operate in a synchronized loop. The framework is built upon four interconnected pillars, moving from the systemic architecture to intelligent, self-optimizing functionalities. Specifically, this chapter aims to:

- Define a modular CPS architecture that serves as the structural foundation for robot-integrated manufacturing cells through the design of modular system workstations.
- Establish a Data Analytics framework for real-time performance monitoring and bottleneck identification, ensuring that reconfiguration is triggered by empirical data.
- Propose a systematic Decision-Making Logic for system reconfiguration, utilizing a matrix-based approach to map product requirements and data restrictions against robotic capabilities.
- Integrate machine vision and Digital Twin-based functionalities to optimize the performance and flexibility of the reconfigured system.

The scope of this methodology is cantered on Collaborative Robot cells and Integrated Robotic Workstations (press brake and quality control units) within a SME environment. The research focuses on the Cyber-Physical bridge – specifically the communication between field-level sensors, edge computing units, and cloud-based monitoring. While the methodology is designed to be scalable, the boundaries of this research are defined by:

- **Technical Scope** – integration of Smart Sensors, Machine Vision, and Adaptive End-Effectors.
- **Operational Scope** – high-variation product environments, necessitating frequent system adjustments.
- **Human-Machine Interaction** - supportive models between human operators and robotic units.

The development steps described in this chapter are built directly on the results and methods presented in Publications I-VI, with each subsection clarifying the specific contribution of the respective papers. By the end of this chapter, a complete methodological framework will be established, providing the theoretical and technical basis for Use-Case Implementations detailed in Chapter 4.

3.1 Cyber-Physical Architecture of Robot-Integrated Manufacturing Cells

This section addresses Task 1 by defining the foundational architecture required for transforming legacy units into interconnected CPS ecosystems. The transition of traditional production workplaces into dynamic, interconnected ecosystem is driven by the convergence of advanced digital technologies and physical automation. The

combination of technologies, such as Smart Sensors, Internet of Things (IoT) (Batth et al., 2018), Machine to Machine Communication (M2M) (Stojmenovic, 2014), and AI-based solutions, has fundamental importance in the further development of existing manufacturing cells.

The next phase for future production workplaces is the implementation of a comprehensive data collection layer that serves as the primary criteria for decision-making within robotic cells. This is achieved by utilizing virtual environments for the processing and management of the physical cell's data. In this thesis, solutions and methods are investigated for upgrading existing production cells to the level of automation and intelligence required by I4.0 standards.

The goal is to define possibilities for evolving existing production systems, as illustrated in Figure 5, to meet I4.0 principles through the application of Smart Sensor technology. Within this CPS architecture, information is collected, processed and controlled by Manufacturing Execution System (MES) (Saenz De Ugarte et al., 2009) to ensure continuous and optimized workflow across the entire production unit.

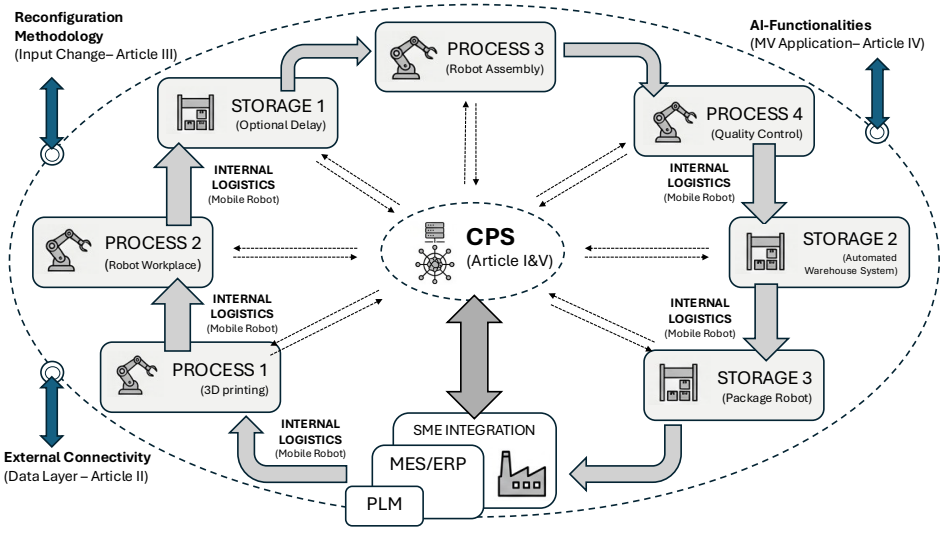


Figure 5. Robot Integrated Manufacturing System – CPS Architecture

To achieve the required agility and intelligence, this CPS framework is analysed through three distinct but interdependent layers, which are addressed in detail in the subsequent sections of this chapter:

1. External Connectivity and Data Layer: Focusing on the real-time harvesting of production data (Section 3.2 and Publication II).
2. Reconfiguration Methodology: Addressing the logic required for rapid system adjustments based on input changes (Section 3.3 and Publication VI).
3. Machine Vision Functionalities: Implementing cognitive tools such as MV for performance and quality improvement (Section 3.4 and Publication III).

3.1.1 Ontology of Modern Manufacturing

In a knowledge-based economy, manufacturing is characterized by continuously shortened product life cycles and increased demands for functionality, quality, and mass customization. Consequently, the strategic orientation toward the development,

improvement, and efficient utilization of production systems has become a prerequisite for industrial competitiveness. As established by Lõun (Lõun, 2010), a company functions as a complex, customer-oriented system where its participation in broader enterprise networks – whether abstract or functional – defines its operational reach.

The ontology of a modern production system is structured around three core pillars: resources, processes, and strategies, as shown in Figure 6. While the physical environment (layout, machinery type, and location) provides the structural base, the functional environment – defined by the technological capabilities of machine tools – dictates the system's actual performance. In the context of this methodology, these technological possibilities evolve through the integration of advanced machinery, including CNC tools, Industrial Robots (IRs), and collaborative robots (cobots).

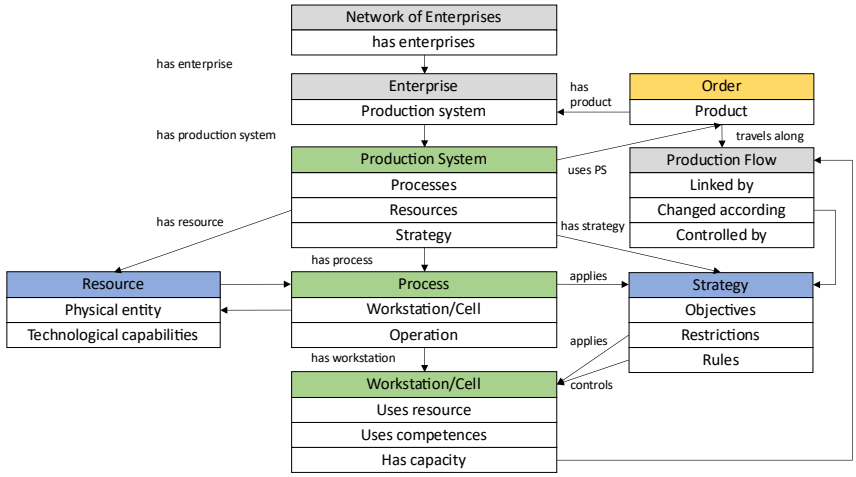


Figure 6. Robot Cell Utilization Ontology in Manufacturing (Lõun, 2010)

Modern manufacturing intelligence is no longer confined to the physical device; it comprises the smart use of networked information to handle demand-dynamic economics. Driven by the convergence of the Internet of Things (IoT) and software-defined architectures, this evolution enables safe, collaborative human-robot interaction within shared physical workspaces. This ontological shift from static machinery to dynamic cyber-physical capabilities forms the basis for the reconfigurable systems discussed in this thesis.

3.1.2 Manufacturing Cell Model

To bridge the gap between conceptual ontology and physical execution, a robust manufacturing cell model is required to evaluate system performance under variable conditions. The model proposed in this research is rooted in a Performance Evaluation Model and implemented through DES (Kangru et al., 2018) using specialized software environments (e.g., Rockwell Automation Arena). An overview of this architectural model is illustrated in Figure 7 and discussed in detail in Publication IV.

The primary utility of the manufacturing cell model is its ability to simulate diverse production orders simultaneously, mirroring real-life industrial complexity. By incorporating order-specific data and operation sequences, the simulation tracks the product's journey from input to completion, including necessary rework cycles. Within the scope of this methodology, concurrent simulation allows for the identification of

structural bottlenecks and the assessment of combined order effects on the system's overall capacity.

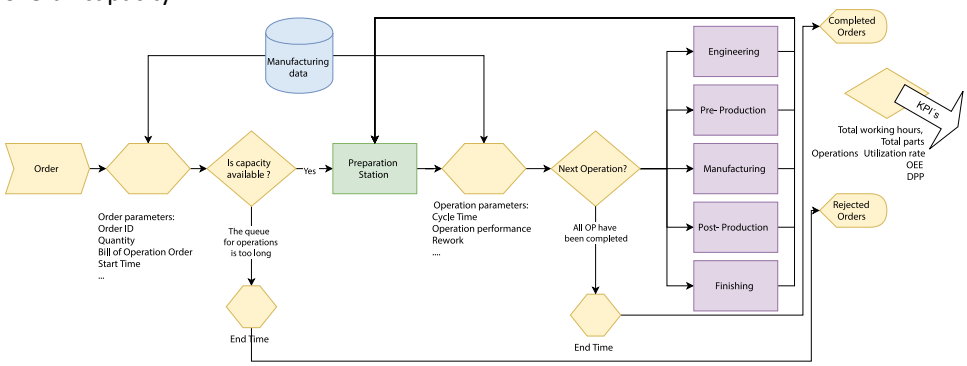


Figure 7. Manufacturing Cell Model (Kangru, Mahmood, et al., 2020)

Furthermore, the model serves as a pre-execution validation tool for reconfiguration. Before any physical changes are made to the cobot cell, the DES environment allows for the testing of new layouts or process parameters. The resulting performance records provide the empirical evidence needed to trigger the reconfiguration logic described in later sections of this chapter.

3.1.3 Integration and Connectivity

The transition toward a fully reconfigurable robotic system requires a shift in manufacturing architecture, specifically regarding the integration of vertical and horizontal value chains. Traditional models, such as those formalized by the ISA-95 standard, typically utilized a rigid 5-layer pyramid where communication was restricted to adjacent levels, as illustrated in Figure 3. However, modern requirements for agility and real-time data analytics have rendered this hierarchical approach insufficient.

In the current Industry 4.0 landscape, integration is driven by distributed computing, edge intelligence, and sophisticated software layers (ERP, PLM, MES, and CAD/CAM). As production has become data-intensive, the focus has shifted toward high-performance networking and embedded edge computing, allowing for decentralized decision-making. Technical innovation is characterized by the implementation of Digital Twin principles, where virtual and augmented reality are used not only in the design stage but also during real-time execution and monitoring (Lydon, 2020).



Figure 8. Lab-scale of Industry 4.0 CPS in TTK UAS

Within the proposed methodology, connectivity is viewed as the nervous system of the CPS. By leveraging real-time analytics, the system moves beyond mere connectivity toward interoperability. This ensures that information from the shop floor (MV, smart sensors) is directly accessible for high-level enterprise planning, creating a seamless loop of continuous improvement and rapid reconfigurability. The proposed architectural integration is executed by the lab-scale Industry 4.0 CPS implementation at the TTK UAS (Figure 8). It serves as the experimental and educational testbed for the use cases presented in current thesis.

3.2 Data Analytics in Manufacturing

The implementation of data analytics on the shop floor is a critical component of modern CPPS. To achieve a fully integrated and reconfigurable robotic cell, as described in the systemic methodology of this thesis, the transition from raw physical data to actionable digital intelligence is essential. This process is facilitated by the Industrial Internet, which utilizes ICT technologies to connect industrial machines, actuators, and sensors to a digital world represented by cloud platforms. This section focuses on Task 2 by establishing a real-time data collection within the framework to enhance process transparency and provide feedback loops within brownfield SME environments.

The introductory framework for this data transition is visualized in Figure 9, which illustrates the multi-layered approach required for real-time shop floor transparency.

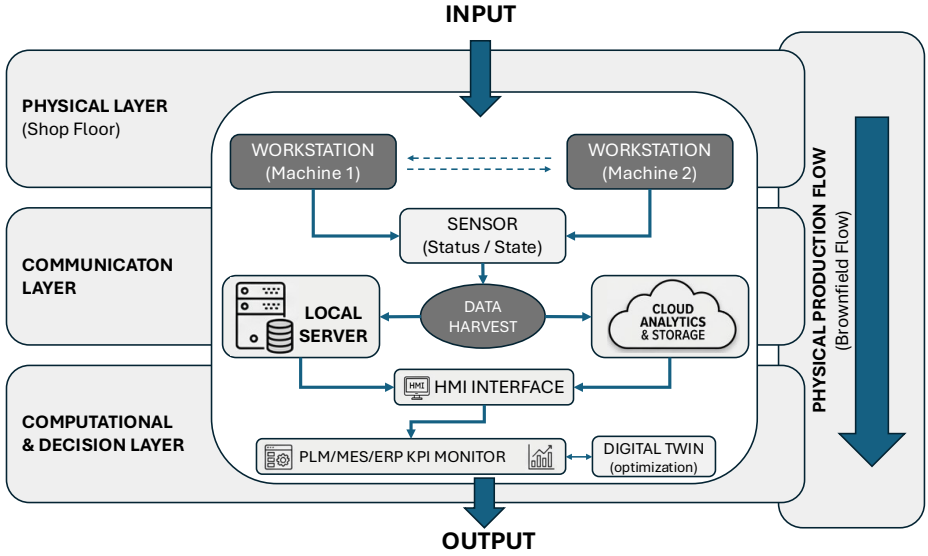


Figure 9. Cyber-Physical Data Flow Architecture

This architecture organizes the manufacturing environment into three functional layers:

1. Physical Layer: workstations and sensors capture the "Status/State" of physical processes.
2. Communication Layer: data harvesting hubs and local servers manage the ingestion and distribution of real-time information.
3. Computational & Decision Layer: cloud analytics, PLM/MES/ERP integration, and Digital Twin simulations process data to monitor KPIs and optimize performance.

The experimental basis for this framework was carried out in collaboration with Alise Technic Ltd, utilizing an industrial robot work cell consisting of a Yaskawa robot, a vacuum gripper, and an Amada CNC press brake. Data collection and integration within this cell were executed using the Dimusa system (described in sub-chapter 3.2.2), a model-based real-time production monitoring and prediction system developed to provide optimal functionality with low investment and integration time.

3.2.1 Data Collection and Integration

The Internet of Things serves as the primary bridge by connecting the physical environment of the SME shop floor to cyberspace, allowing electronic components distributed throughout the workplace to function as a unified cyber-physical infrastructure (Yang et al., 2018). This integration enables the company's ERP and warehousing systems to exchange data with production equipment, facilitating a single management ecosystem (Kindness, 2025).

A central objective of this data integration is the application of KPIs, which provides executives with a high-level, real-time view of production progress and bottleneck identification. For the robot press brake workstation specifically, the production cycle time is utilized as the primary KPI. As established in Publication II, real-time monitoring of cycle times allows for a comprehensive assessment of the statuses of both the individual robot and the press brake equipment. The selection of KPIs for different companies and different levels is generally a problem for deciding on some criteria, and the choice must be as problem oriented as possible (Kaganski et al., 2017; Kangru, Mahmood, et al., 2020; Kibira et al., 2018). The operation cycle time indicates the time required to perform a bending operation at the workplace.

The operation cycle time (T_{cycle}) can be expressed as the summation of specific operational phases:

$$T_{cycle} = T_{bending} + T_{robot} + T_{idle} + T_{setup} \tag{3.1}$$

Where $T_{bending}$ is the active time when the Amada press-brake or the quality control unit is performing the work. T_{robot} is the time used by the robot for moving parts, positioning and changing grippers. T_{idle} are the waiting times caused by delays in material feeding or synchronizing between the robot and the machine or smart fixture. T_{setup} is the time needed to adjust the system, which is a key factor when evaluating how fast the cell can be reconfigured.

In addition to cycle times, the methodology uses the OEE framework to measure the performance of the system. OEE is calculated using three factors (Jonsson & Lesshammar, 1999):

$$OEE = Availability\ (A) * Performance(P) * Quality(Q) \tag{3.2}$$

Where,

$$Availability\ (A) = \frac{Planned\ production\ time - Unplanned\ downtime}{Planned\ production\ time} \tag{3.3}$$

$$Performance\ (P) = \frac{Actual\ amount\ of\ production}{Planned\ amount\ of\ production} \tag{3.4}$$

$$Quality\ (Q) = \frac{Actual\ amount\ of\ production - non\ accepted\ amount}{Actual\ amount} \tag{3.5}$$

It is particularly relevant in HMLV environments, where frequent changeovers and material-handling disruptions significantly effect productivity (Snatkin et al., 2013). In this research, data analytics is used to improve the Performance part of the OEE. By finding small stops and optimizing the robot's movements, the system aims to reduce T_{robot} and T_{idle} times, which increases the total output of the cell.

To make sure the collected data is accurate, validation logic is used at the edge level. Sensor signals are checked against the robot controller's status to avoid errors caused by electrical noise. For example, the signal from a vacuum gripper relay is only accepted as "true" if it happens at the correct step in the robot program. A mathematical expression of validation:

$$S_{valid} = S_{relay} \cap S_{program_step} \tag{3.6}$$

This ensures that only correct and synchronized data is sent to the Dimusa system, providing a solid input for simulation and further optimization.

3.2.2 The Structure of Collected Data and Application

Based on the cycle time formula (Eq. 3.1), the robot press brake cell is divided into two main monitoring targets: the robotic manipulator and the press brake. Both units are equipped with an IoT platform to enable synchronized real-time data collection.

At the Amada press brake station, the system measures the time for vertical movements of the press-brake, focusing on active process time and idle intervals. Simultaneously, for the Yaskawa robotic device, specific actions are tracked, including object grabbing and releasing, positioning, and waiting times at the feeding table. By monitoring these specific components, the methodology identifies which part of the process has the greatest impact on the overall cycle time, providing direct input for future optimizations. Production Monitoring System (PMS) concept selection is discussed in the following studies (Eiskop et al., 2017; Snatkin et al., 2013).

To capture this data without interfering with the existing machinery control, two types of sensors are used:

1. Non-invasive clip-on ammeters: These are installed on the incoming power phases of both the robot and the press-brake. By monitoring current consumption, the system can distinguish between when the equipment is actively working (processing) and when it is in standby mode.
2. Relay circuits: These are integrated into the control systems to capture operational movement data. For the press-brake bending, relays provide information on the upper and lower limit positions of the stamp. For the robot, relays monitor when a part is captured by the vacuum or magnetic gripper and track when the gripper reaches specific programmed points.

This sensor data is processed by the Dimusa system, which is a model-based production monitoring tool developed at TalTech. Dimusa is specifically chosen for this methodology because it offers a low investment cost and short integration time, making it highly suitable for SME environments. It provides a flexible monitoring and prediction framework that can be reconfigured according to the specific needs of the production process.

An efficient real-time information flow within the Dimusa system includes the collection of the following data points:

- The operational condition of the equipment – KPI hierarchy, level III and II.
- Real-time production data and order fulfilment status – level III and I.
- Material flow and product quality indicators – level III and I.
- Process-specific data, including error sequences and their causes – level II.

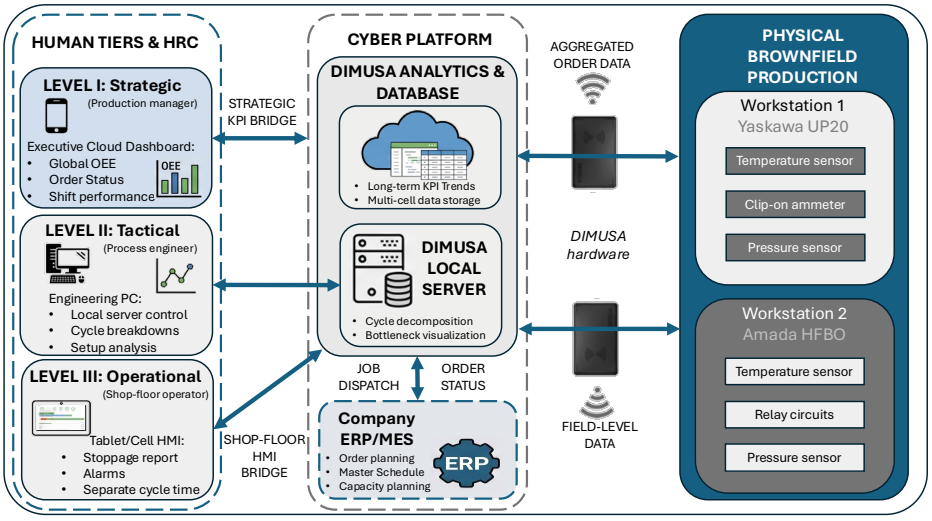


Figure 10. Cyber-physical retrofitting architecture coupling brownfield equipment with multi-tiered decision levels via the Dimusa platform

Data collected from the production line is contextualized within the system to deliver actionable operational intelligence. As shown in Figure 10, the Dimusa system establishes a cyber-physical bridge between the physical shop floor and higher-level management systems. Field-level signals captured by non-invasive sensors are ingested via dedicated Dimusa hardware and transmitted to the cyber platform, where the local server and analytics database perform cycle decomposition and KPI calculation. This architecture synchronizes order status with the company ERP/MES and routes role-specific data across three decision tiers: strategic performance tracking for plant management (Level I), process and bottleneck diagnostics for engineers (Level II), and real-time cycle telemetry and stoppage reporting for shop-floor operators (Level III).

3.3 The Methodology of Reconfigurable Cobot-Based Production

This section details the proposed methodology for reconfiguring existing robotic systems, moving from the systematic architecture and data layers previously established to the operational decision-making logic. The core of this methodology is a structured pathway, as illustrated in Figure 11, for identifying a need for reconfiguration on the shop floor. The need for the process is triggered in two primary scenarios: when the monitoring system (PLM/MES/ERP) based on KPIs identify poor execution rate or the change of product requirements – new or revised product. This initiates a reconfiguration analysis loop, where constraints such as data restriction, product features, and equipment capabilities are assessed.

The assessment is concentrated on three constraint groups, stated above:

1. Data constraints – performance, quality, cycle time, idle time.
2. Product features – size, shape, weight, assembly type.
3. Equipment capabilities – degrees of freedom (DOF), reach, payload, precision.

These three groups are a representative subset; the full variable list is system-dependent and scalable. Proposed modularity allows human decision-makers to prioritize parameters based on specific product complexity and brownfield requirements, ensuring the methodology remains an indicative decision-support framework.

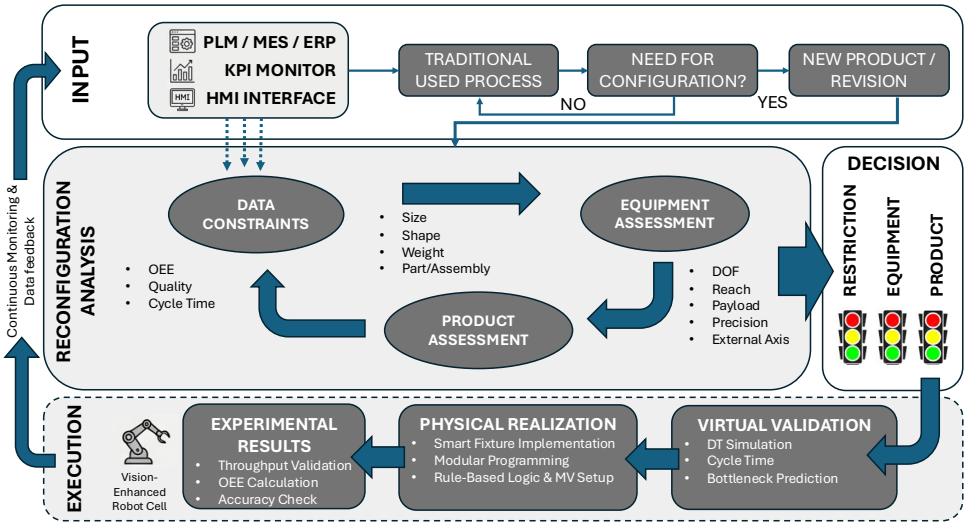


Figure 11. Reconfiguration Decision-Making Logic Concept

The proposed reconfiguration methodology is an indicative decision-support framework triggered by product-driven changes or performance optimization. While monitoring systems (PLM/MES/ERP) and data constraints provide empirical triggers, the final decision remains with the user. This ensures that reconfiguration aligns with broader operational goals and SME-specific resource constraints rather than functioning as a self-executing autonomous loop.

The Execution block, dashed boundary in Figure 11, defines the transition from theoretical design to the practical implementation detailed in Chapter 4. This phase follows a rigorous sequence:

1. Virtual Validation: Using Digital Twin analysis to mitigate implementation risks.
2. Physical Realization: Deploying vision-enhanced hardware and modular programming.
3. Experimental Evaluation: Measuring the actual impact on OEE and throughput.

A critical feature of this architecture is the feedback loop back to the Input stage, ensuring a continuous lifecycle of data-driven monitoring and iterative optimization. To demonstrate this methodology, the following subchapters describe the operational framework of a robotic unit in an IoT module manufacturing environment, building directly upon the contributions of Publication VI.

3.3.1 The Framework of Robot Unit in Company

The successful integration of a collaborative robotic unit requires a systematic alignment with the company's existing production hierarchy. In HMLV manufacturing, production procedures are often complex, combining highly automated lines for primary processing with manual labour for delicate secondary operations. To illustrate this methodology, Figure 12 presents a conceptual framework of a production system divided into distinct functional levels. Typically, such workflows begin with an automated level for standard assembly, followed by a human-operated level for tasks requiring high dexterity and cognitive judgment. The proposed methodology introduces a third, collaborative level into this hierarchy, intended to automate specific bottlenecks – such as manual quality control – where critical metrics are often left undocumented. To successfully reconfigure an existing manual workstation into this cobot-based system, it is essential to systematically evaluate the environment, the manual workplace, and the existing workflow. Specific evaluation methods regarding Human-Robot Collaboration and the work environment are discussed in detail in Publication VI.

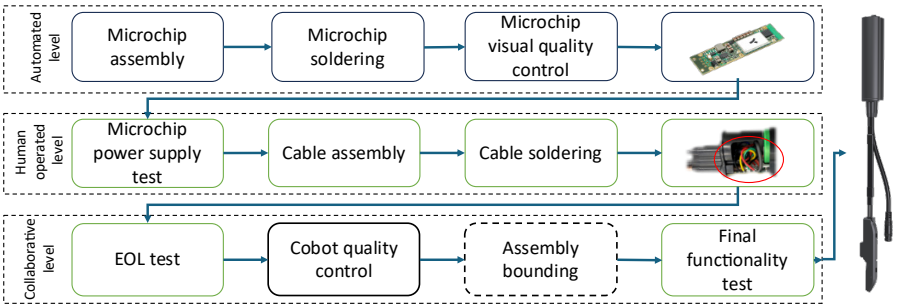


Figure 12. Production levels in a Company

As illustrated in the conceptual layout in Figure 13, the workstation is organized into three functional areas: the input, process, and output areas. The input area serves as a buffer where human operators stack various products to prepare them for processing.

The process area is the core of the collaborative cell and handles the most complex tasks of the cycle. This stage involves the robotic manipulator picking up individual workpieces and placing them into an integrated smart fixture. Once secured, the system executes the designated automated tasks, such as multi-position machine vision inspections or component verification, depending on the product variant. After the cycle is complete, the robot releases the workpiece and transfers it to the output area.

The output area is logically divided into two routing sections: conforming finished products and non-conforming defective items. Defective products can be further categorized by type to determine whether they should be routed for rework or disposal.

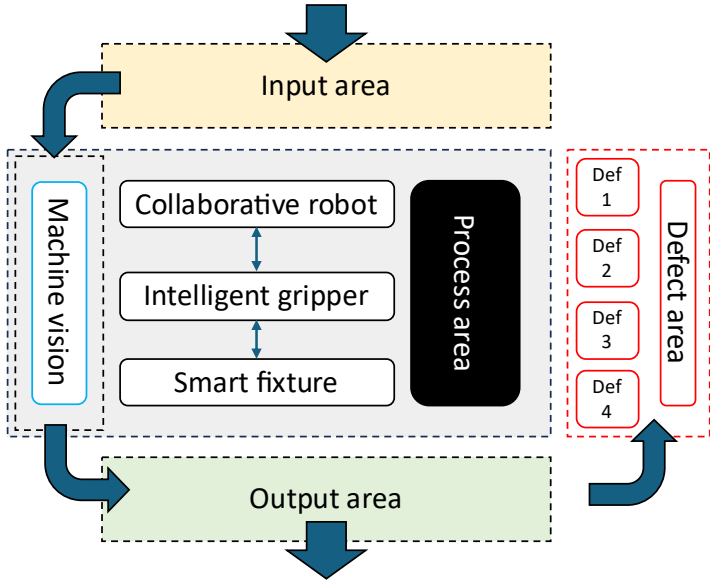


Figure 13. The Concept of Reconfigured Robot Cell for Quality Control

Another significant aspect of the proposed system is Human-Robot Collaboration, which introduces a third, collaborative level into SME production. HRC is expected to enhance both production quality and operational efficiency (Kalimuthu et al.). This collaboration involves several critical factors, including safety, regulatory compliance, technical potential, and ergonomics.

The transition to a collaborative environment requires preparatory training for operators and a designated testing period. Following this phase, further analysis can be conducted to refine the HRC logic if necessary. The model proposed by Oberc, illustrated in Figure 14, serves as a guideline for SME management to implement training programs and subsequent performance analysis (Oberc et al., 2019). This structured approach ensures that the human operator is effectively integrated into the reconfigurable robotic cell, fulfilling the collaborative principles of Industry 5.0.

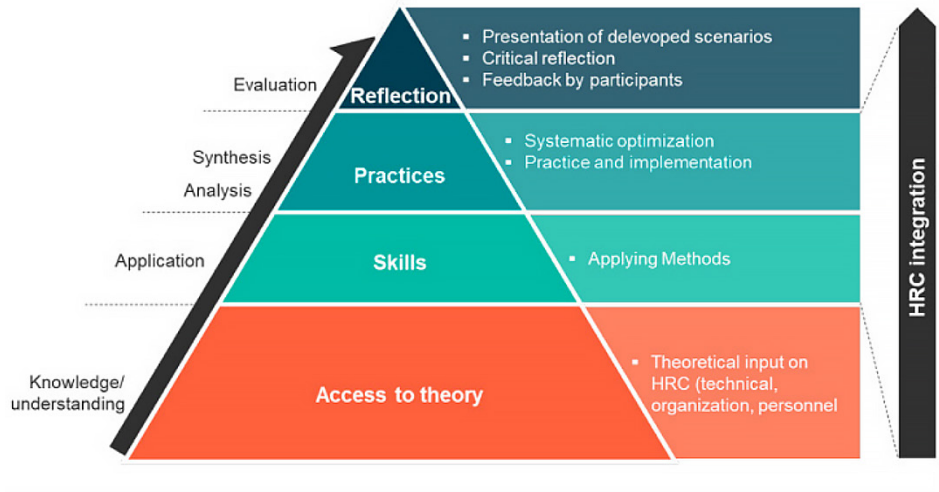


Figure 14. HRC Training Cycles (Oberc et al., 2019)

3.3.2 The Product Evaluation Procedure

The following section describes the importance of product analysis and its necessity within the reconfiguration framework. A product can be characterized by various features, including size, shape, colour, weight, material, assembly type (part or assembly), and the presence of soft or rigid elements. When redesigning or reconfiguring a production system, it is essential to evaluate which of these features have the most significant impact on the system's requirements.

Building on the research of Paramasivam, who presented design methods that can be applied to the system redesign process, this methodology utilizes the PEM (Paramasivam & Senthil, 2009). The application of the PEM is a key element of Task 3, providing the logic for rapid reconfiguration as sought in RQ3. While a standard PEM is typically an M x M matrix, current thesis proposes a simplified version specifically tailored for the needs of SMEs. This simplified approach maps product features against their system effects to allow for a quick evaluation during the reconfiguration analysis loop. The specific product-based features and their effects are presented in Table 4.

Table 4. Simplified Evaluation of Product Features

Feature/Effect	No Effect	Small	Moderate	Vast
Size				x
Shape				x
Colour	x			
Weight			x	
Material		x		
Part/Assembly			x	
Quantity		x		
Soft/Rigid Elements				x

By mapping these product features against their system effects, the simplified PEM provides a structured logic to evaluate product families during the reconfiguration

analysis loop. Identifying critical parameters – such as part rigidity, flexible components, or complex geometries – directly dictates the subsequent selection of adaptive end-effectors and defines the functional requirements for modular smart fixturing.

3.3.3 Existing Robot Cell and Smart Equipment

The existing robotic cells apply limitations to the reconfiguration outcomes. The structural and functional configuration of the collaborative workstation must balance product envelope dimensions, peripheral footprint, and human ergonomic requirements. Within this methodology, instead of procuring new equipment, robotic manipulators are integrated. Their selection and cell integration follow four core design criteria:

1. **Workspace and Reach Allocation:** The repurposed manipulator's kinematic reach must encompass peripheral loading stations, optical inspection zones, and defect sorting buffers while maintaining a central collaborative envelope that leaves sufficient unobstructed workspace for manual operator tasks.
2. **Ergonomic Workstation Positioning:** Product input and output fixtures are specified at standard human operational heights, minimizing operator bending and physical strain during manual batch transfer.
3. **Controller Interface and Protocol Modularity:** To ensure reconfigurability without rewriting fundamental safety or motion control routines, the robot controller must provide scalable general-purpose digital and analogue I/O alongside standard industrial communication buses (such as Modbus TCP/RTU, Ethernet, or serial interfaces). This decouples peripheral sensor signals from the internal kinematics of the robot.
4. **Mechanical Modularity:** The workstation chassis is specified around standardized modular structural framing (e.g., industrial aluminium extrusion profiles). This provides structural rigidity and positional repeatability during manipulation while allowing fast, non-destructive mechanical reconfiguration when introducing new product families to the legacy setups.

By synthesizing these spatial, ergonomic, and interface criteria, the workstation functions as an adaptable physical node within the reconfigurable manufacturing cell. This structural baseline ensures that mechanical adjustments between product variants do not compromise operator safety or require structural redesign, establishing the necessary physical foundation to deploy the collaborative control workflow on previously existing hardware.

3.3.4 Smart Fixture Logic and Integration

The complex product topologies often set strict limitations on fixture design. Due to the high variety of products in SME environments, work-holding devices must be adaptable enough to facilitate machine vision detection from multiple angles without requiring full tool changeovers. Consequently, the methodology proposes a smart fixturing logic designed to ensure multiple distinct indexing positions for comprehensive optical inspection.

The operational principle of the smart fixture is divided into three main phases, as illustrated in Figure 16:

1. Clamping Process (CP): The cobot places the workpiece into the fixture. The fixture then clamps the product to ensure a stable and accurate position, exposing the necessary features for inspection.
2. Quality Control Process (QCP): The system executes the inspection sequence. The fixture actively indexes the product between multiple pre-defined positions to allow the machine vision system to verify all required functional surfaces or components.
3. Unclamping Process (UNP): Once the inspection is complete, the fixture returns to its primary home position, unclamps, and releases the product for the cobot to transfer it to the output area.

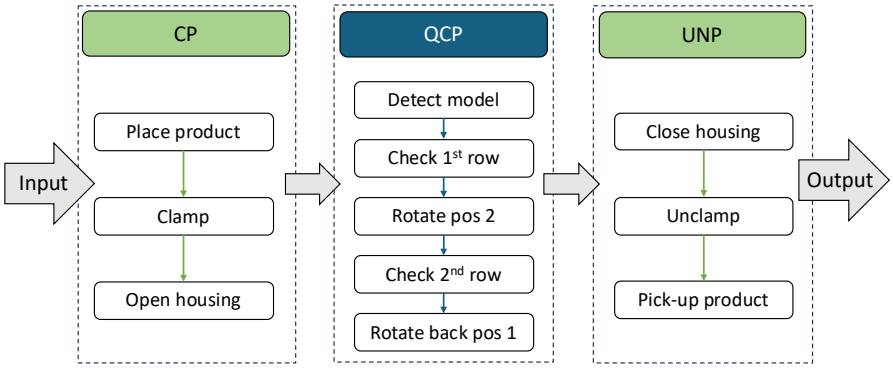


Figure 15. The Principle of the Smart Fixture

All communication and synchronization between the fixture, the MV system, and the robot are managed through the cobot system controller, ensuring a seamless integration of the smart hardware within the reconfigurable cell architecture.

3.3.5 Design Procedures and Modern Manufacturing Techniques

Building on the functional logic of the workstation, the physical realization of the smart fixture must utilize a combination of modular assembly and advanced fabrication principles to meet the flexibility requirements of high-mix environments. To ensure compatibility and rigidity, the fixture framework should be constructed utilizing standardized industrial aluminium profiles, matching the architecture of the main robotic cell.

To achieve multi-angle inspection capabilities without manual intervention, the methodology dictates the integration of an automated rotational or indexing mechanism synchronized directly with the cobot's controller. Figure 16 illustrates a conceptual embodiment of these design principles, demonstrating how a standardized base frame can be integrated with a rotary mechanism, adjustable camera mounts, and interchangeable tooling.

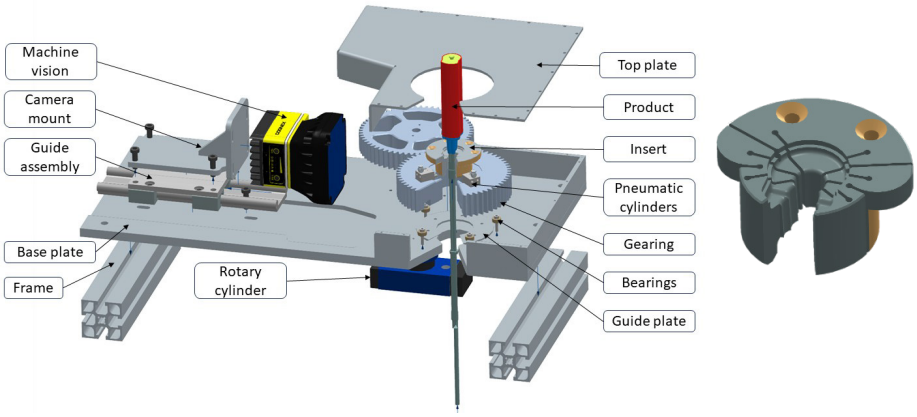


Figure 16. A Conceptual Design of the Modular Smart Fixture

Furthermore, the design of the product-holding inserts relies fundamentally on additive manufacturing principles (Berman, 2012; Wuest et al., 2016). This technique provides the geometric freedom to create complex, customized features – such as internal pockets, flexible clamping walls, and narrow slots tailored to specific product families, as seen in the insert detail in Figure 16. Additive manufacturing ensures that when a new product variant is introduced, only the low-cost modular insert needs to be redesigned and replaced, while the primary mechanical structure and actuation mechanisms of the fixture remain unaltered. Finally, the optical inspection system must be mounted on adjustable guide assemblies. This mechanical modularity allows for precise focal, distance, and spatial reconfigurations to accommodate diverse product geometries and lighting requirements.

In conclusion, synthesizing the Product Evaluation Matrix with modular additive manufacturing principles provides a structured, highly adaptable engineering framework for SME production environments. This methodology not only reduces the lead time required to fabricate fixtures for new product variants but also physically maps product constraints to required robotic capabilities. Ultimately, this modular hardware setup establishes the necessary physical foundation for integrating the rule-based machine vision and decision logic functionalities discussed in the following section.

3.4 Machine Vision Functionalities in Cobot-Based Manufacturing for Performance Improvement

This section represents the integration of the previously established layers—the data-driven foundation (Section 3.2) and the reconfigurable physical hardware (Section 3.3) – into a cohesive, intelligent system. The focus here shifts to the operational engine of the robotic cell: MV-driven functionalities that leverage real-time data to optimize performance and handle production uncertainties.

Figure 18 presents the comprehensive architecture of the proposed integrated framework. It serves as a methodology map for the entire system, illustrating the continuous synchronization loop between the Physical Application (shop-floor hardware and sensors) and the Virtual Application (the digital twin and logic engines). By bridging these domains, the system moves beyond static automation toward an adaptive manufacturing unit, which is discussed in Publication III.

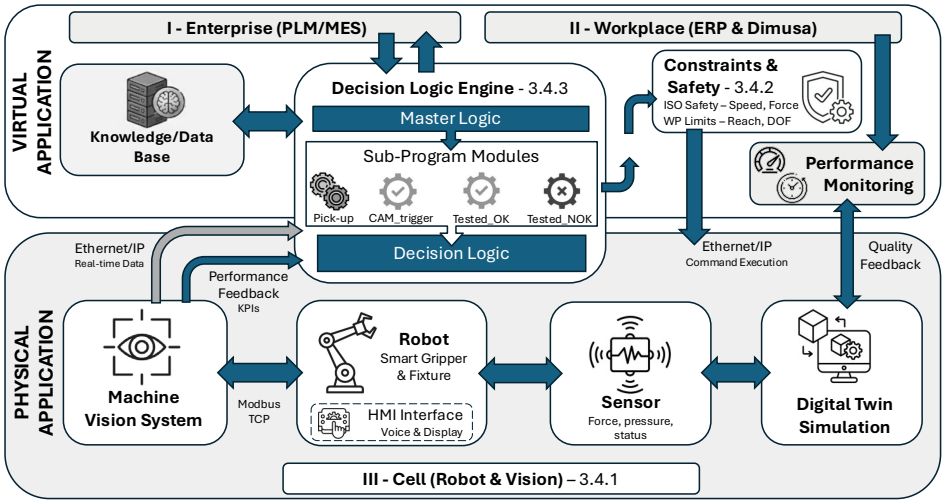


Figure 17. The Application of Vision-Based Workstation

The proposed architecture relies on three primary pillars to achieve performance improvement in a HMLV environment:

1. System Communication (3.4.1): the hierarchical connectivity that enables seamless data exchange between the robot, vision system, and enterprise layers (ERP/MES).
2. Configurable System Limitations (3.4.2): the definition of safety and technical boundaries that govern autonomous decision-making and ensure operational reliability.
3. Programming Structure (3.4.3): the modular software architecture that allows for rapid logic reconfiguration and enhanced human-robot interaction.

By establishing this integrated framework, the system can autonomously adapt its behaviour to new product variants while maintaining the high standards of quality and efficiency required in modern SME production.

3.4.1 System Communication

To enable intelligent functionalities within a reconfigurable manufacturing environment, communication is structured across three levels: enterprise, workplace, and robotic cell.

At the enterprise level, high-level planning aligns PLM, ERP, and MES systems (Figure 6). At the workplace level, the Dimusa system tracks equipment status and operational KPIs (Figure 9). Within the robotic cell itself, communication coordinates the robot, the smart fixture, and the machine vision system in real time.

Data exchange within the cell relies on two primary channels:

1. Digital I/O: Dedicated digital inputs and outputs handle time-critical signals, such as fixture clamping verification, part presence detection, and cycle triggers. This ensures that robot movements only occur when physical clamping is confirmed.
2. Industrial Network Protocols: Standard protocols (such as Modbus TCP/RTU and Ethernet TCP/IP) transfer model selection data, inspection triggers, and pass/fail results between the robot controller and the vision system.

Using standard protocols and modular I/O signals allows the cell to switch between different product variants without altering the basic communication setup. The physical implementation of this communication architecture, including the specific controller interfaces and network settings, is detailed in Section 4.3.1.

3.4.2 Configurable System Limitations

While the communication protocols and physical I/O ports define the connectivity of the system, several higher-level limitations dictate the boundaries of vision-driven performance optimization. Within the university laboratory environment, these constraints are categorized into hardware-bound and operational-logical limitations:

- Computational Latency: The use of Modbus TCP/RTU for data exchange between the Cognex vision system and the Omron controller introduces a specific latency. For machine vision applications - such as real-time pass/fail defect detection via Modbus or adaptive cycle adjustment – this delay defines the minimum cycle time. The system must operate within these timing constraints to ensure that data remains synchronized during rapid reconfiguration.
- Collaborative Safety Constraints: As a cobot-based unit, the system is governed by safety standards such as ISO 10218-2 and ISO/TS 15066, regarding force and speed monitoring. Automated algorithms aimed at performance improvement cannot exceed these safety-rated monitored speeds. This creates a performance limitation where the system must balance maximum throughput with human-operator safety in the shared workspace.
- Software Interoperability: Utilizing software such as TMFlow and In-Sight Explorer creates a semi-closed environment. The ability of an external vision system to dynamically alter robot paths or vision parameters is limited by the pre-defined command set of the controllers. Consequently, reconfiguration is focused on "switching" between pre-validated program blocks rather than generating entirely new autonomous behaviours in real-time.

These limitations are not static; they are configurable parameters in the system's ontology. Recognizing these boundaries is essential for the programming structure described in the next section, ensuring that performance improvements remain within safe and technically feasible limits.

3.4.3 Modular Programming Logic and Workflow Architecture

To enable rapid reconfiguration in HMLV manufacturing without low-level software redevelopment, the operational sequence is decomposed into modular, task-specific functional blocks. This architecture isolates core handling steps from quality inspection decisions, establishing a deterministic control loop.

As conceptualized in Figure 18, the control logic governs the interaction between physical execution and autonomous decision-making:

- **Standard Execution Sequence:** Operational tasks – including home positioning, part pick-up, trajectory transfer, and fixture loading – are structured as discrete, callable modules executed sequentially.
- **Inspection Synchronization:** The execution halts motion during the inspection phase, where a trigger (CAM_trigger) initiates optical verification.

The manipulator remains stationary or transitions to an unload posture while the vision system evaluates the workpiece.

- **Closed-Loop Decision Modules:** The inspection result is processed via two decision modules that govern subsequent material routing:
    1. Conforming components trigger the acceptance sequence (Move_OK >> Tested_OK), advancing the part to the downstream buffer.
    2. Non-conforming components are diverted into an exception handling route (Move_NOK >> Tested_NOK), isolating the defect from the main production line.
- **Execution Continuity and Restart Control:** Following part routing, the supervisory logic evaluates termination conditions (Condition continue vs Condition END). If the batch run is incomplete, the system prompts the loading of a new workpiece and resumes the cycle automatically without manual software resetting.

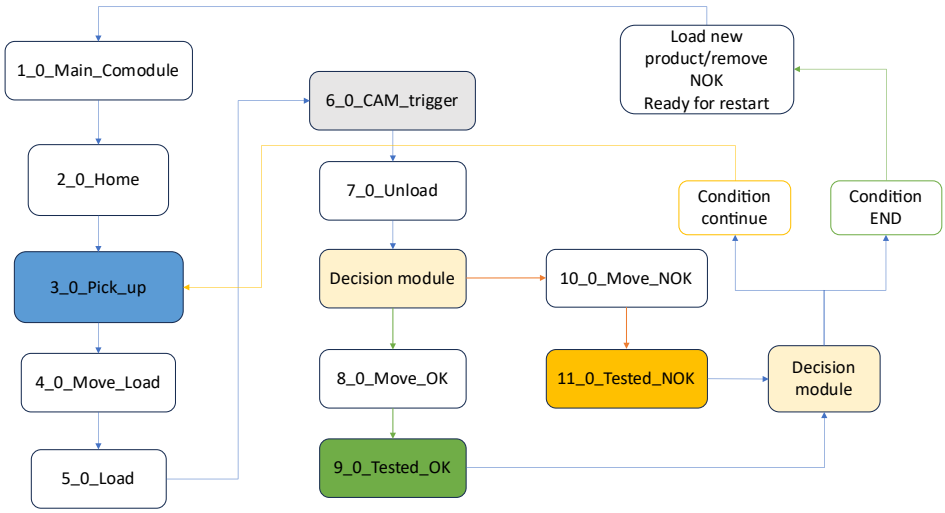


Figure 18. Schematic Overview of the Modular Programming Logic

This structured workflow decouples handling trajectories from quality inspection outcomes, providing a standardized baseline adaptable to diverse robotic controllers and peripheral sensors. Within this generalized logic, human-robot collaboration (HRC) is integrated at defined supervisory nodes, most notably during workpiece reloading and exception clearing (Load new product / remove NOK / Ready for restart). While Figure 18 establishes the vendor-neutral control logic and decision boundaries, the specific multi-modal HRC interaction mechanisms – such as acoustic state signalling, graphical operator prompts, and collaborative pause states—are implemented at the execution layer, as detailed in Section 4.3.2, in Figure 25.

The integration of data-driven inspection and decision logic completes the reconfigurable methodology, linking the modular hardware architecture established in previous sections to actionable operational control. As synthesized in the overarching

framework of Figure 17, the system's primary capability lies in translating physical shop-floor states into validated operational decisions.

The core operational outcomes of this architecture are structured across three criteria:

1. Data-Driven Responsiveness: Continuous vertical data exchange across physical, control, and supervisory tiers enables the system to adapt to production variations and batch changeovers in real-time.
2. Safety-Compliant Operation: Collaborative interaction thresholds and bounded kinematic parameters ensure that cycle optimization never compromises established industrial safety envelopes.
3. Standardized Modularity: Hierarchical software decomposition reduces reconfiguration downtime, directly complementing the mechanical flexibility of modular tooling and smart fixtures.

This integrated framework ensures that the manufacturing cell achieves flexible, deterministic reconfigurability across both hardware and software layers, establishing a practical foundation for human-centric cyber-physical systems under Industry 5.0 principles.

3.5 A Practical Guide for SMEs: Reconfiguration Roadmap

To bridge the gap between theoretical frameworks and shop-floor reality, the methodology developed in Chapter 3 is distilled into an actionable, cross-sectoral reconfiguration roadmap. This guide is designed for SME production managers and process engineers to systematically execute cyber-physical retrofitting on legacy equipment, utilizing the logic established in Figure 11.

1. **Identify the Trigger – the Input Phase:** Reconfiguration must be driven by empirical data or product changes rather than arbitrary decisions.
    - Performance Trigger: Monitor shop-floor KPIs by integrating fundamental data acquisition tools (e.g., non-invasive sensors). A consistent performance drop or a spike in idle time signals a structural bottleneck.
    - Product Trigger: The introduction of a new product variant or a design revision necessitates a shift in manufacturing capabilities.
    - **Action**: If either trigger is activated, initiate the Reconfiguration Analysis loop.
2. **Execute the Reconfiguration Analysis – the Assessment Phase:** Evaluate the boundary constraints using the Product Evaluation Matrix (PEM).
    - Data Constraints: Define the target parameters for the new setup (required cycle time, acceptable defect rate, target OEE).
    - Product Assessment: Use the PEM to map the new product's physical features (size, shape, rigidity, assembly complexity).
    - Equipment Assessment: Compare the product requirements against the legacy robotic cell's capabilities (Degrees of Freedom, maximum reach, payload limits, precision).
    - **Action**: Identify the exact capability gaps between the existing hardware and the new product requirements.
3. **The Decision Gate:** Evaluate the overlapping constraints from Step 2.
    - If the existing hardware can fulfil the product requirements within the established safety and physical envelopes, proceed to Execution.
    - If fundamental equipment limits are exceeded, a completely new cell design is required rather than a reconfiguration.
4. **The Execution Pipeline - Virtual to Physical Piloting:** Execute the modernization in a strictly sequenced pathway to minimize shop-floor downtime.
    - Virtual Validation: Feed operational times into a Digital Twin. Test layout changes and robot trajectories to locate bottlenecks before physical implementation.
    - Rapid Prototyping: Deploy the modular hardware. Whenever possible, utilize Additive Manufacturing technologies to accelerate the piloting phase. Implement rule-based machine vision and standard industrial communication protocols.
    - Modular Programming: Program the robot using task-oriented visual modules. Isolate handling movements from the pass/fail decision logic to ensure operators can easily adjust parameters for future batches.

5. **Experimental Evaluation and Piloting**
    - Conduct a physical pilot run to validate throughput against the Digital Twin prediction.
    - Evaluate the new setup based on core performance indicators: processing speed, output quality, operational safety, and economic feasibility.
    - Feed this new operational data back into the monitoring dashboard, closing the cyber-physical loop.
6. **Final Evaluation and Production-Grade Upgrade**
    - If the experimental pilot results from Step 5 meet the required operational and economic targets, the temporary setup must be finalized for continuous production.
    - **Action:** Upgrade the rapidly prototyped components, reconfigured equipment, and temporary fixtures to production-grade standards, ensuring necessary precision, wear resistance, and long-term durability for production cycles.

3.6 Summary of Framework and Design Methodology

In conclusion, the engineering frameworks and design methodologies developed in Chapter 3 establish the theoretical foundations and functional blueprints required to design and deploy reconfigurable cyber-physical workstations in brownfield environments.

The cyber-physical architecture formalized in Section 3.1 addresses Task 1 by structuring the manufacturing environment into three functional layers: an external connectivity and data ingestion layer, a modular reconfiguration methodology layer, and an automated decision and quality control layer.

Section 3.2 formalizes the field-level data analytics framework to support Task 2 and address RQ2. This is achieved by establishing the mathematical formulation for operational cycle-time decomposition alongside machine availability metrics. To ensure data integrity against electromagnetic and mechanical noise inherent to brownfield production, edge-level signal validation logic (S_{valid}) was formulated, ensuring that only verified operational machine states are ingested into the Dimusa monitoring platform.

The reconfiguration decision-making methodology detailed in Section 3.3 fulfills Task 3 and directly addresses RQ3. To manage product variety in HMLV scenarios, this framework employs a simplified PEM that systematically correlates critical workpiece features with required manufacturing transformations. This decision logic governs the physical design principles of reconfigurable tooling:

- Establishing multi-position indexing mechanisms to enable multi-angle inspection accessibility within a single workstation.
- Utilizing Additive Manufacturing principles to produce modular, rapid-change inserts tailored to product geometries while ensuring stable physical clamping without structural fixture redesign.

Finally, the supervisory control logic established in Section 3.4 satisfies Task 4 by formalizing the closed-loop interaction between optical inspection and collaborative manipulation. Workstation safety and execution envelopes are bounded by collaborative robotics standards (ISO 10218-2 and ISO/TS 15066) and external device communication latency. To operate reliably within these constraints, Section 3.4.3 establishes a modular,

hierarchical control architecture that decouples task coordination, human-in-the-loop exception handling, and physical trajectory execution.

Collectively, these architectural, mechanical, and algorithmic models provide the vendor-neutral framework necessary to systematically retrofit brownfield equipment. They define the structural baselines that directly govern the empirical implementations and industrial case studies validated in Chapter 4.

4 Implementation and Experimental Results

This chapter presents the physical implementation, simulation analysis, and experimental validation of the reconfigurable cyber-physical framework developed in Chapter 3. The primary objective is to evaluate the practical feasibility, operational agility, and performance impact of the proposed design methodology inside real-world manufacturing environments. Specifically, this research investigates how real-time data acquisition, digital twin simulations, and modular machine vision systems can resolve the structural and software integration bottlenecks typical of brownfield SMEs.

The empirical validation of the proposed methodology is systematically verified through specific industrial use-cases that transition from discrete machine-level data tracking to high-mix collaborative automation. The experimental evaluations are executed through a three-stage sequential pathway, as shown in Table 5:

1. CPPS and Data Integration (Section 4.1): Testing the vertical integration of legacy production hardware with cloud-based platforms using the ERP and MES framework to establish shop-floor data transparency.
2. Digital Twin and Throughput Simulation (Section 4.2): Constructing a high-fidelity DES model to analyse throughput optimization, execute risk-free "what-if" planning, and perform bottleneck analysis based on real-time stochastic inputs.
3. Vision-Enhanced Reconfigurable Cell Validation (Section 4.3): Deploying a physical Cobot-Based Quality Control testbed to evaluate the reliability, execution accuracy, and hardware-software interoperability of safe collaborative setups under variable product configurations.

The application domains covered in this dissertation are strictly constrained to discrete manufacturing processes within high-mix, low-volume SME environments. The implementation and efficiency of the proposed methodology directly depend on a specific discrete KPI framework, primarily cantered on operation cycle time breakdowns and relies on OEE variables. These application boundaries are represented by the two empirical use-cases evaluated in this chapter: robotized material handling and machine-state synchronization in sheet metal bending, and modular assembly positioning with vision-based sequence classification in electronics/IoT quality inspection – the pathway of experimental progression is shown in Table 5.

Table 5. Experimental Reference Matrix

Section	Focus Area	Technical Methods & Tools	Key Metrics & Targets	Output Value
4.1 CPPS Integration	Legacy hardware connectivity	MES, LAN/WiFi, M2M, RFID	Traceability, Zero data loss	Baseline data for cell
4.2 Simulation & DT	Virtual validation & optimisation	Visual Components, DES, Dimusa data integration	Cycle time reduction, Throughput time	Locate bottlenecks
4.3 Reconfigurable Cell	HRC interoperability & autonomous quality control	Omron TM5-900, Robotiq gripper, Cognex 2D-MV, Smart Fixture	Batch size, Defect rate, Failure rate	Safety reliability according to ISO 10218:2023

Consequently, specific industrial domains are excluded from this research scope due to fundamental differences in operational metrics, production logic, and capital structures. High-volume mass production environments are excluded because automated lines focused on low-mix production operate on long-running, unchanging economies of scale where rapid product-driven modifications or "batch size 1" agilities are logistically unnecessary. Furthermore, large-scale corporations are outside the scope because these enterprises possess the financial capital to deploy proprietary, custom factory-wide automation architectures supported by dedicated internal engineering teams, which makes a low-cost, open-protocol brownfield retrofitting methodology tailored for resource-constrained SMEs redundant within their specific operational frameworks.

By defining these precise boundaries, the experimental results provide a targeted proof-of-concept for scalable, low-cost automation cells operating under physical brownfield constraints.

4.1 Implementation of CPPS Integrated Manufacturing

The practical validation of the methodology begins with the implementation of the Cyber-Physical Production System architecture, bridging the gap between theoretical definitions and shop-floor reality. As established in Publication I, the system is designed for autonomous operation, where the hierarchy between enterprise planning and physical execution is strictly maintained through a decentralized communication logic.

4.1.1 Autonomous Operation and Control Logic

The realized system utilizes a top-down information flow where incoming orders are planned within the ERP system, while the sequence of production operations and M2M communication is managed at the MES level. A key feature of this implementation, as illustrated in Figure 19, is the independence of individual units. While all devices are connected to the MES via LAN or Wi-Fi, they operate autonomously without requiring constant polling from a higher-level program.

The MES serves as a command distributor: it issues "start" commands and waits for execution confirmations before distributing subsequent tasks. This decentralized approach ensures that the system remains robust; if a device encounters an error, a

report is forwarded to the MES, which then makes real-time decisions regarding parallel production paths or workstation reassignment based on the number of details required.

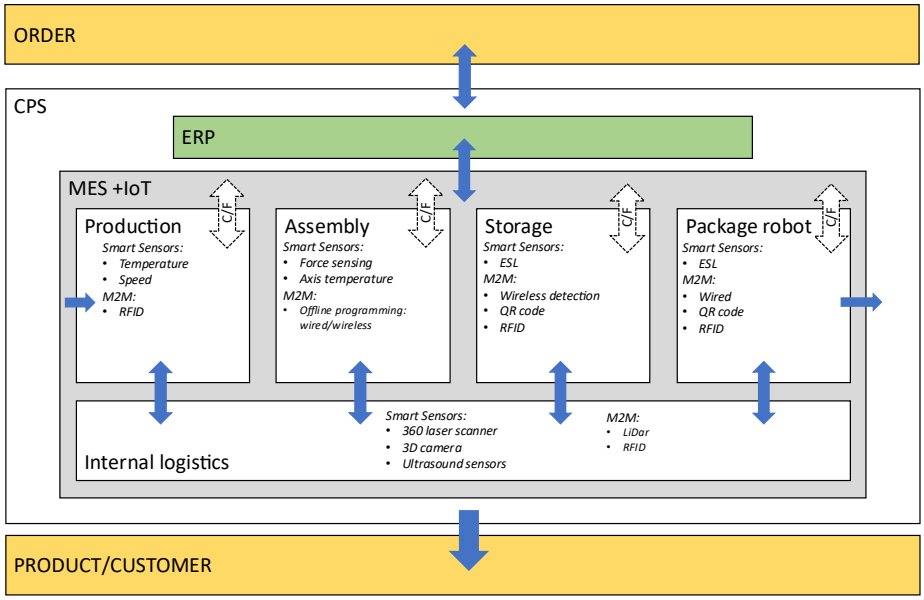


Figure 19. Developed System Schematic Diagram

The implementation of the CPPS structure and RFID-based tracking (Section 4.1.2) addresses RQ2 by demonstrating how integrated data analytics improve transparency and serve as a trigger for system reconfiguration.

4.1.2 Data Acquisition and Tracking

To move from pure control to the performance monitoring discussed in Publication II, the physical layer was equipped with specific sensing technologies to provide real-time feedback:

- Local Monitoring: Each workstation utilizes photoelectric sensors (PNP output) (Omron Corporation, 2021) to monitor local status. This feedback is first processed by local PLCs and then transmitted to the MES to manage synchronized unit movements.
- RFID Traceability: A critical component of the CPS is the integration of RFID technology (Want, 2006). Each production plate and storage box is equipped with an RFID chip (Siemens Corporation, 2021), allowing the MES and individual units to maintain live information on product locations and process history.
- Flexible Reconfiguration: Following Industry 4.0 principles, the system design allows for the addition of new equipment (e.g., mobile robot arms) without major adjustments to the central control system.

The implementation at Alise Technic demonstrated that this CPS structure successfully supports high-mix production. By combining the autonomous control logic of Publication I with the granular monitoring capabilities of Publication II, the environment provides a

stable and data-rich foundation for the robotic reconfiguration tasks analysed in the following sections.

4.2 Simulation and Digital Twin Analysis

This use-case closes the loop on a specific part of the framework rather than on the framework as a whole. The data acquisition and signal validation layer defined in Section 3.2 was derived from this same press brake cell, and the present section feeds that validated data into a Digital Twin in order to exercise two further elements of Chapter 3: the performance-driven entry path of the reconfiguration decision logic in Figure 11, where a KPI deviation rather than a product change initiates the analysis loop, and the Virtual Validation step of its execution block. The product-driven path of the same logic is not exercised here and is validated separately in Section 4.3.

The hardware accordingly differs from the collaborative workstation that serves as the reference implementation in Sections 3.3 and 3.4. Instead of an Omron TM5-900 cobot with an adaptive gripper, a smart fixture and 2D optical inspection, this cell is a fenced Yaskawa UP20 industrial manipulator with a vacuum gripper serving an Amada HFBO press brake, with no vision subsystem and no collaborative operating mode. Because the monitoring layer had to be attached without modifying the legacy controllers, machine states are captured non-invasively through clip-on ammeters and relay circuits rather than through the robot controller. This contrast is deliberate: it tests whether the architectural and data layers of the proposed methodology remain applicable across robot classes, vendors and safety regimes, while the collaborative and product-driven layers are validated on the cobot cell in Section 4.3. The real-time data collected from the CPPS environment (see Section 4.1) serves as the stochastic input for high-fidelity simulations. By creating a DT of the manufacturing unit, it is possible to experiment with different production scenarios and layout configurations without the risks and costs associated with physical downtime. In this thesis, Visual Components software was utilized to develop a tailor-made digital environment that identically mirrors the physical press brake cell, as shown in Figure 21.

In this experimental context, the Digital Twin acts as a predictive advisory tool for 'what-if' analysis. Triggered by the T_{idle} bottleneck (Section 3.2.1), the simulation empowers the human expert to validate reconfiguration outcomes virtually, balancing efficiency gains against long-term system stability.

4.2.1 Virtual Model Construction and Input Validation

To ensure the virtual model reflects reality, it was populated with actual performance data from the Dimusa Monitoring Panel (Figure 20). While the monitoring panel provides a broad overview of equipment availability and OEE, its primary role in this simulation context is to provide accurate cycle time distributions and resource states.

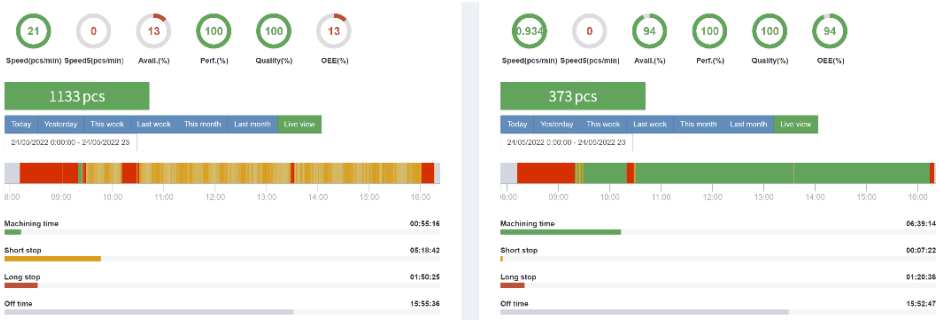


Figure 20. Dimusa Monitoring Panel – Amada HFBO (left), Yaskawa UP20

The press brake cell's "AS-IS" process flow was mapped by observing the physical interaction between the Yaskawa UP20 robot and the Amada HFBO press brake. The sequence involves:

1. Picking a blank sheet.
2. Repositioning the blank on a dedicated table.
3. Loading the blank into the machine.
4. Bending, unloading, and palletizing.

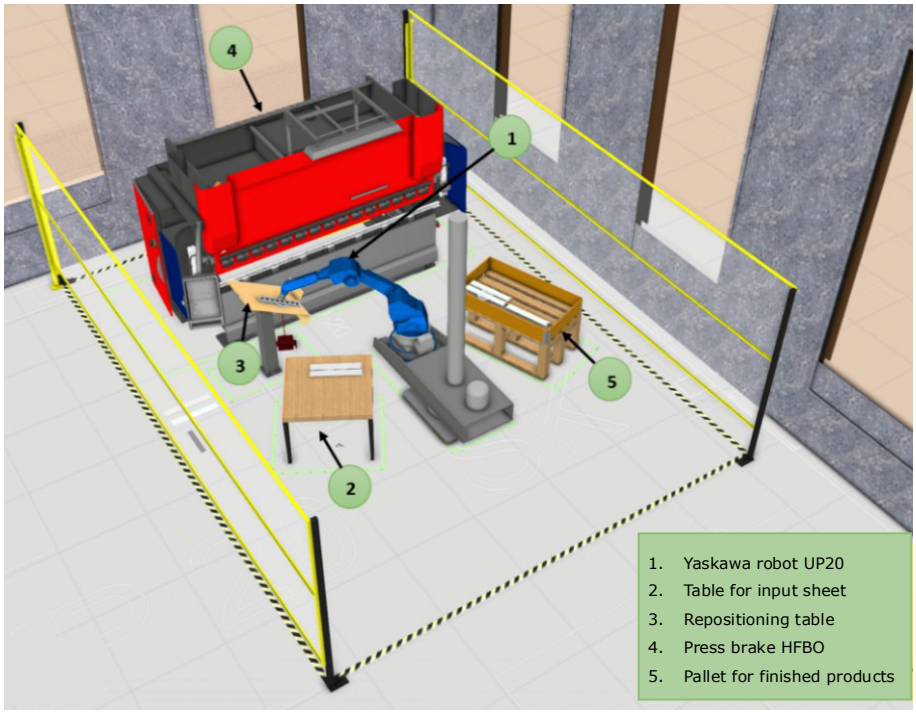


Figure 21. Virtual Simulation Model of the Press Brake Cell in 3D Environment

4.2.2 Throughput Analysis and Simulation

The Digital Twin was used to validate a reconfiguration hypothesis: the elimination of a non-value-added activity. Throughput can be defined as the number of parts passing through the process per unit time. In this press brake cell, the throughput is the bent

parts collected on average in the pallet as finished products for a certain time-period. It can be formulated as:

$$Average\ Inventory\ (I) = Throughput\ (R) * Average\ Flow\ Time\ (T) \qquad (4.2)$$
$$R = \frac{I}{T}$$

Where,

I – is bended parts produced,

T – is the total process time,

R – is the throughput of the cell.

Two scenarios were tested in a 1-hour simulation run:

- Scenario 1 (AS-IS), as illustrated in Figure 21: Current layout including the repositioning table, where the robot's cycle time is extended by manual-like handling logic.
- Scenario 2 (TO-BE): Optimized layout where the robot picks the part in a way that eliminates the need for a separate repositioning step, allowing for a more direct flow to the press brake. This can be executed using MV.

The comparison of the expected throughput over a 60-minute period is illustrated in Figure 22. The "TO-BE" scenario demonstrates a consistent lead over the "AS-IS" state. The cycle time was reduced approximately 19% (from 21,2 to 17,2 seconds), which results in a 23% increase in steady-state throughput (from 170 to 209 pieces/hour).

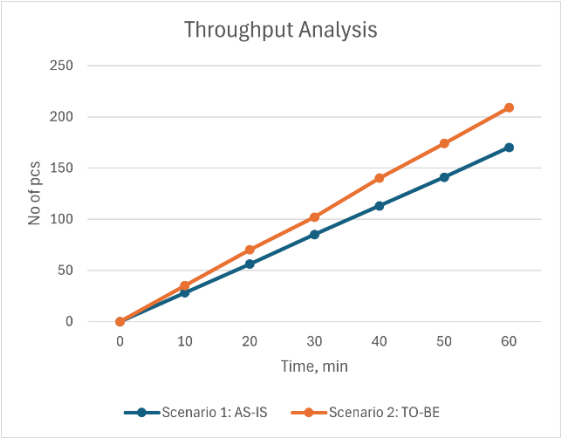


Figure 22. Comparative Throughput Analysis: AS-IS vs TO-BE

4.2.3 Bottleneck Analysis and OEE Impact

The integration of Dimusa parameters with the simulation results allows for a detailed breakdown of the cell's performance. A critical finding from the monitoring data was the press brake's technical speed of 21 bends/min. The simulation revealed that in the AS-IS state, the robot's handling time - specifically the repositioning - acted as a primary bottleneck, preventing the machine from reaching its full potential.

Table 6. Comparative Performance and Bottleneck Analysis

Metric / KPI	Unit	Scenario 1: AS-IS	Scenario 2: TO-BE	Difference
Throughput	pcs/h	170	209	+23%
Cycle Time	s	21,2	17,2	-4,0
Performance	%	67	83	+16
Primary Bottleneck	-	Repositioning Table	Machine Vision	-
Robot Utilization	%	66	64	-2

The simulation results confirm that the removal of the repositioning activity—identified as redundant through Digital Twin analysis—leads to an increase in throughput from 170 to 209 pieces/hour. By streamlining the robot's motion, the bottleneck is shifted from the handling sequence back to the actual manufacturing process. Interestingly, this optimization allows for higher output with slightly lower robot utilization (64% vs 66%), indicating a more efficient and less busy system. This validates the use of DT as a risk-free tool for testing reconfiguration strategies before physical implementation.

While the digital model validates the 23% performance gain in a virtual setting, realizing these improvements in a physical environment require a fundamental change in how robotic cells are configured. Specifically, the elimination of the repositioning table necessitates a more advanced and adaptive method of part handling and fixing. These

results directly address RQ1 and Task 5, quantifying the value-add of eliminating non-value-added activities through Digital Twin validation.

To bridge this gap between virtual optimization and physical reality, Section 4.3 details the implementation of the proposed Reconfiguration methodology into physical robotic cells. This hardware-level solution is designed to execute the optimized logic identified in this simulation, enabling the robotic cell to achieve the predicted throughput while maintaining the flexibility required for high-mix production.

4.3 Implementation and Validation of the Vision-Enhanced Reconfigurable Cell

Following the virtual performance optimization in Section 4.2, this section focuses on the physical realization of a CBQC system. Some of the system's hardware components are repurposed from the assembly line (robot, controller, gripper), while others have been added to the system (machine vision with software, a smart fixture and industrial fixtures). By validating the rule-based machine vision logic in a physical setting, this use-case fulfills Task 4 and provides empirical evidence for RQ4 regarding system interoperability and HRC. This implementation serves as the primary proof-of-concept for the synergy between reconfigurable hardware (Publication VI) and automated optical inspection features (Publication III).

4.3.1 Experimental Setup and Hardware Integration

The experimental validation of the proposed vision-enhanced methodology was conducted in partnership with an SME operating in the IoT sector, focusing on micro-mobility components such as zero-emission vehicles. The existing quality control procedure for their products was strictly manual. To validate the reconfiguration framework developed in Chapter 3, a CBQC workstation was physically deployed to automate the inspection of complex IoT modules.

Applying the Product Evaluation Matrix (established in Section 3.3.2) to the target IoT module identified significant physical constraints. Evaluating the product based on the PEM criteria revealed that the most critical features for the current system were size, shape, and soft/rigid elements, followed by assembly complexity.

In terms of size and geometry, the target IoT module has an irregular shape and a specific length-to-diameter ratio, which makes it challenging to handle with a standard collaborative robot setup. The product is a complex assembly consisting of shell-type elements, cables, connectors, a circuit board assembly, and a battery. This type of assembly, featuring flexible and delicate components, is not typical for standard pick-and-place assignments. Figure 23 presents the physical dimensions and shape of the IoT module, highlighting the specific constraints that governed the subsequent hardware selection for the reconfigured robotic cell.

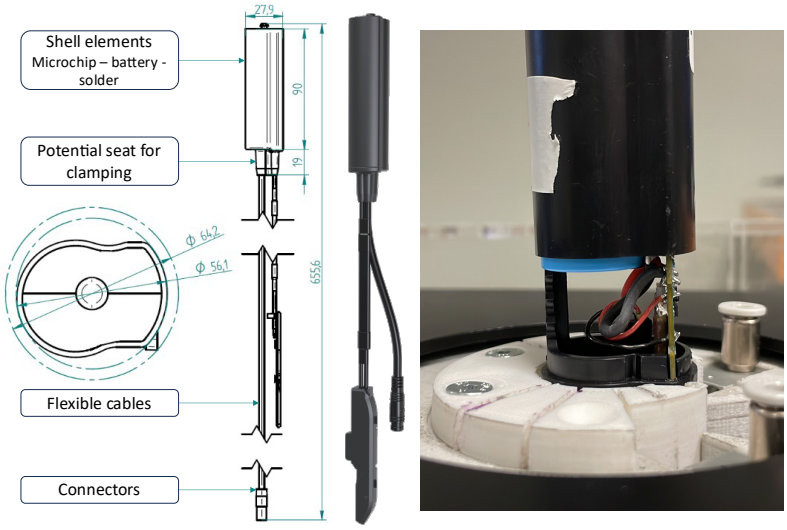


Figure 23. The Size and Shape of the Product

Based on these product constraints, the physical implementation of the Cobot-Based Quality Control (CBQC) workstation was designed according to the criteria established in Section 3.3.3. To establish a structured inspection workflow, both the physical setup and virtual model are organized into four distinct functional zones: input, process, output, and defect quarantine, as initially conceptualized in Figure 13 and physically realized in Figure 24.

The process zone forms the core of the workstation, integrating the following hardware and software components:

- **Robotic Manipulator**: An Omron TM5-900 collaborative robot (900 mm reach) repurposed from an existing educational conveyor line, providing kinematic envelope coverage across all four zones while preserving operator clearance.
- **End-Effector & Tooling:** A repurposed Robotiq 2F-140 adaptive parallel gripper capable of handling the delicate shell elements of the IoT module.
- **Smart Fixture:** Fabricated based on the proposed modular methodology, the custom-designed fixture utilizes a pneumatically controlled rotary cylinder allowing 0- to 180-degree transitions via spur gears. Clamping is achieved via pneumatic cylinders applying a 10 N force to secure the product within custom 3D-printed modular inserts.
- **Optical Inspection System:** A Cognex In-Sight 7905C 2D-vision system equipped with directional illumination, mounted on a manual guide assembly for precise focal adjustments.
- **I/O and Networking:** Workstation external devices interface through the robot controller's 16 digital inputs/outputs, 2 analogue inputs, and 1 analogue output, utilizing Modbus TCP and standard Ethernet protocols for data exchange.
- **Software Tools:** Omron TMFlow governs robot path execution and collaborative logic, Cognex In-Sight Explorer configures machine vision processing routines, and ModPoll is used for Modbus communication diagnostic testing.

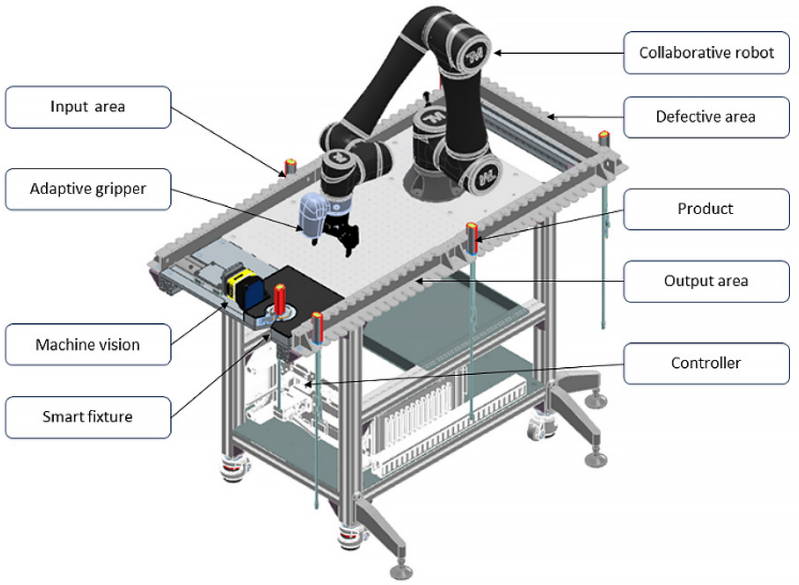


Figure 24. Quality Control System Layout and Model

Because the system was reconfigured into an existing production footprint with predefined physical boundaries. We used repurposed hardware components augmented with new machine vision and smart fixturing, it serves as true brownfield reconfiguration case rather than newly purchased greenfield installation. Consequently, RoboDK simulation software was utilized for preliminary layout design and kinematic path verification. This virtual pre-validation ensures collision-free trajectories and confirmed collaborative safety limits within the constrained workspace prior to physical deployment.

4.3.2 Implementation of the Modular Programming Architecture

The generalized control logic defined in Section 3.4.3 was physically instantiated within the collaborative inspection cell using the Omron TMFlow graphical programming environment. In HMLV manufacturing, conventional text-based robot programming introduces extensive setup delays and necessitates specialized engineering expertise, often forming a bottleneck for SMEs (Materna et al., 2018). To mitigate this, visual programming structures and modular subroutines significantly reduce the cognitive load on operators, enabling reconfiguration without complex code editing (El Zaatari et al., 2019).

The master program structure was organized into sequential case modules governed by execution flags, as depicted in Figure 25:

- Initialization and Operator Cues (CASE_V0 – CASE_V10): System variables, gripper clearance limits (Birglen, 2019), and communication parameters are initialized. To support safe HRC, the program integrates visual prompts (Display1, Display2) and acoustic signals (Voice1, Voice3). These cues provide clear shop-floor feedback regarding operational states, cell readiness, and cycle initiation.
- Task Execution (CASE_V2 – CASE_V6): Robotic motions are compartmentalized into dedicated routines (2_0_Home through 5_0_Load).

At CASE_V6, the controller sends an execution command to the Cognex 7905C camera (6_0_CAM_trigger) via Modbus TCP and pauses motion until inspection decision is returned.

- Decision Routing (CASE_V7 – CASE_V11): Logic evaluation at Gateway2 steers the manipulator. Based on the binary inspection, the robot either executes the pass sequence via CASE_V9 (9_0_Tested_OK) or routes non-conforming product into the quarantine zone via CASE_V11 (11_0_Tested_NOK). Status registers (SET3, SET4) provide real-time decision to the supervisory system.
- Batch Accounting and Termination (CASE_V15): The termination module registers completed cycles (Cycle_count), verifies batch quantities via Gateway3, and safely stops the cell upon batch completion or operator command.

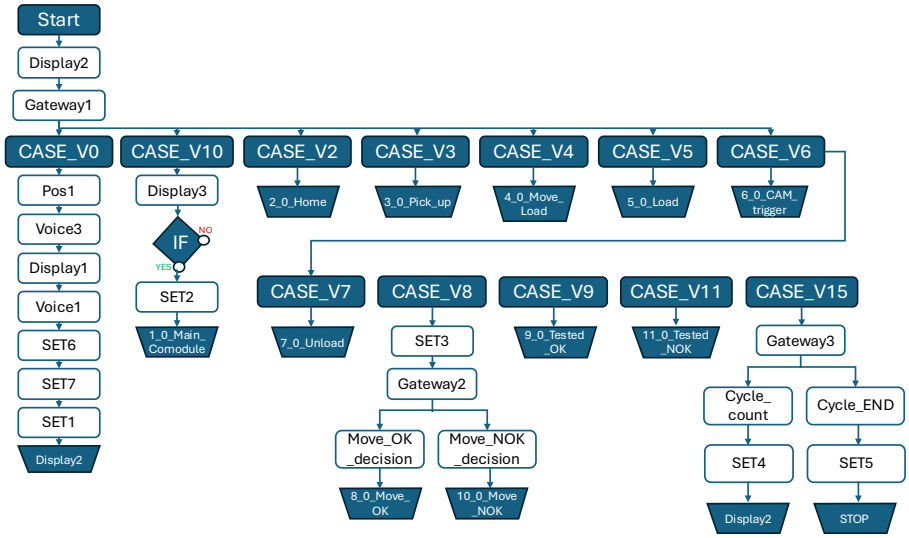


Figure 25. Implementation of the Master Program and Modular Execution Logic

Empirical testing verified that this modular architecture allows rapid adjustments to individual process parameters – such as gripper opening widths or camera trigger delays – within isolated blocks without re-teaching global trajectories or recompiling the master logic. By isolating complex robot motions within predefined modules, the architectural design aims to lower the technical barriers for shop-floor personnel, theoretically facilitating safer and more intuitive batch changeovers without requiring deep programming expertise.

4.3.3 Machine Vision Logic and Parametrical Setup

The vision system triggering is executed via the cobot controller's digital outputs, evoking specific inspection jobs. To validate the product from multiple angles, the smart fixture rotates the part to 0-degree and 180-degree positions.

The inspection task focused on a product with 12 coloured cables - 6 per side. To ensure reliability under varying conditions, a colour database was developed:

- Colour Training: Each cable underwent training in different light conditions and constraint setups.
- Pixel Counting Constraints: As shown in Figure 26, upper and lower boundary variations were defined for pixel counting to determine the "True/False" status of each colour.
- Decision Loop: Feedback is sent to the cobot via digital inputs. A "True" value (1) indicates a successful check, while "False" (0) triggers the decision module to divert the part to the defective area.

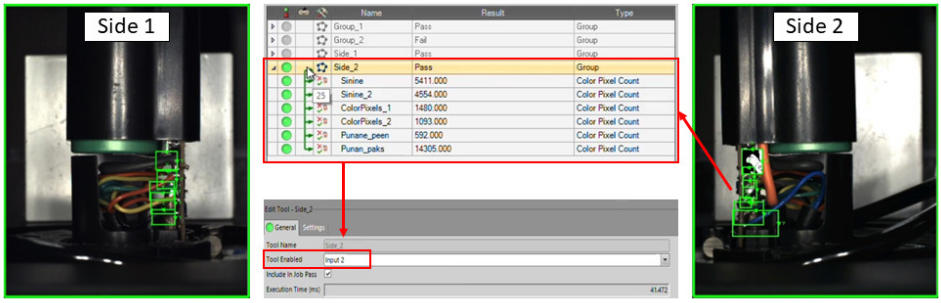


Figure 26. An Example of Machine Vision Program Structure

The physical testing, as shown in Figure 27, involved the random placement of three different IoT module models, with a total of 350 products tested. The motion speed was set to 40% (280 mm/s), resulting in a total cycle time of 90 seconds per product.

The experimental results revealed the following performance benchmarks:

- Handling Efficiency: The adaptive gripper jaw design successfully handled all variants without damaging the products. The motion inside the smart fixture and detection consumed only 2 seconds for both sides - including 200 ms for specific object detection.
- Fail-Safe Behaviour: The decision logic is conservative by construction - a colour that cannot be verified against its trained threshold returns False and routes the product to the quarantine zone, so the inspection gate defaults to rejection rather than acceptance. This property follows from the control structure defined in Section 3.4.3 and is independent of sample size. The campaign inspected 350 units drawn from normal production across three module variants and did not include a controlled number of seeded defects; within this sample no defective unit was observed to pass the gate. The campaign therefore demonstrates handling reliability, cycle time and the conservative behaviour of the inspection gate, but it does not establish a defect-detection rate. Quantifying detection performance requires a sample with a known defect count, which is identified as a limitation in Section 5.1.
- Environmental Sensitivity: As is standard for 2D optical inspection, the system requires controlled illumination. Ambient daylight variations during testing caused approximately 8% of conforming units to be rejected. These units were quarantined rather than passed, which is consistent with the conservative behaviour described above. Controlled lighting is an elementary industrial prerequisite rather than a limitation specific to the proposed methodology. The methodologically relevant constraint is the size of the reference database

behind the rule-based thresholds, which bounds both the achievable detection rate and the tolerance to illumination drift (Section 5.1).

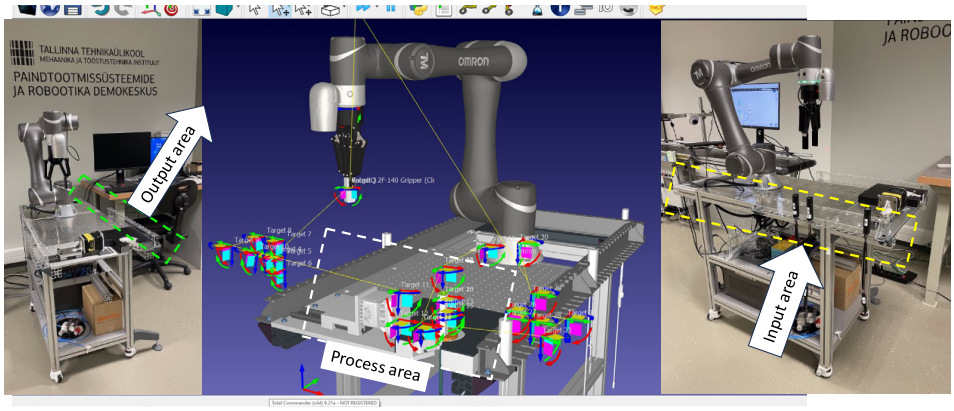


Figure 27. Virtual and Physical Cobot Based Quality Control System

4.4 Summary of Results

In conclusion, the experimental results presented in Chapter 4 provide the empirical validation required to systematically answer the core research questions and verify the assigned tasks. First, the practical implementation of the CPPS architecture in Section 4.1 successfully addresses Task 1 and Task 2 while providing a direct answer to RQ2. This was achieved by deploying a decentralized control logic via an MES command distributor and integrating RFID-based tracking. This setup demonstrated that legacy field-level hardware can achieve autonomous M2M communication and real-time shop-floor data ingestion without requiring constant central polling or inducing system downtime.

Second, the simulation and digital twin analysis in Section 4.2 fulfills Task 5 and resolves RQ1 by quantifying the exact performance impact of removing non-value-added handling activities. The high-fidelity virtual environment validated a 23% increase in throughput, elevating total output from 170 to 209 pieces per hour. This gain resulted from a continuous operation cycle time reduction from 21,2 to 17,2 seconds, which successfully shifted the primary cellular bottleneck from the robot's repositioning sequence back to the active manufacturing machine cycle.

Finally, the physical use-case validation of the reconfigurable cell in Section 4.3 satisfies Task 4 and RQ4 by testing the interoperability of the CBQC ecosystem under industrial safety standards. Physical testing covered 350 randomly placed products across three distinct IoT module variants. Approximately 8% of conforming units were rejected under variable daylight, confirming that the logic is conservative and environment-sensitive. Because the sample was drawn from normal production and did not contain a controlled number of seeded defects, this establishes the conservative behaviour of the decision logic within a single setup rather than a quantified defect-detection rate. The synchronized hardware and modular programming executed the multi-angle verification loop within 2 seconds per product, which included a 200 ms specific object detection window. Collectively, these technical metrics transfer the proposed design methodology from a conceptual framework into an applicable and adaptable manufacturing solution.

5 Conclusions and Future Work

This dissertation presented a comprehensive, knowledge-driven design methodology for transforming legacy robotic cells within SMEs into I5.0-ready Advanced Manufacturing systems. By systematically executing the defined research roadmap, the primary objectives have been successfully achieved, providing distinct answers to the formulated research questions. To answer RQ1, the execution of Task 1 established that low-cost cyber-physical retrofitting provides the highest value-add for brownfield facilities. As validated in Publication I, the strategic integration of open communication protocols combined with smart auxiliary hardware serves as an ecologically and financially sustainable alternative to complete equipment replacement, effectively overcoming hardware-bound legacy limitations. Similarly, to address RQ2, the real-time data collection framework developed under Task 2 significantly enhances shop-floor process transparency. The empirical results published in Publication II demonstrate that low-level machine signals can be successfully aggregated into high-fidelity metrics, proving that operational cycle time and OEE function as dynamic, automated triggers capable of initiating real-time cell reconfigurations.

Furthermore, to resolve RQ3, the systematic reconfiguration methodology developed in Task 3 successfully facilitates the transition from rigid to flexible manufacturing setups. Detailed in Publications VI and IV, the formalization of the Product Evaluation Matrix, when synchronized with Digital Twin virtual validation, provides a reliable predictive environment that allows SMEs to map product features to equipment capabilities and validate new workflows before physical deployment, thereby drastically minimizing changeover downtime. Finally, to answer RQ4, the deployment of automated vision functionalities and safety protocols in Task 4 successfully ensured both system interoperability and safe Human-Robot Collaboration. As documented and validated in Publication III through a cobot-based quality control use-case, rule- and threshold-based machine vision features for pass/fail quality inspection can be seamlessly integrated under the harmonized ISO 10218:2023 standards using simplified, modular software structures and standard industrial interfaces (Modbus TCP) that eliminate the need for specialized coding expertise.

The contribution of this dissertation to the manufacturing landscape lies in formalizing a scalable, low-cost methodology that bridges the gap between enterprise-level digital frameworks and floor-level legacy equipment constraints. While contemporary literature focuses heavily on factory-wide cyber-physical architectures within capital-rich enterprises, this research demonstrates that the principles of Industry 4.0 and 5.0 can be effectively compressed and executed at the localized workstation level. Beyond the specific experimental use-cases of automated sheet metal bending and vision-based electronics quality control, the developed methodology is structurally generic and applicable across a wide spectrum of discrete manufacturing domains. Specifically, any high-mix, low-volume production cell characterized by frequent changeovers, modular tooling modifications, or sequential human-robot activities can utilize this framework. Potential application areas include collaborative mechanical assembly lines, component sorting and packaging units, robotic welding or soldering stations, and automated machine-tool loading cycles. By anchoring the reconfiguration logic to universal discrete metrics and open communication protocols, the methodology allows diverse manufacturing sectors to systematically retrofit legacy equipment without requiring bespoke software development or complete infrastructure replacements.

The scientific novelty of this doctoral research is established through the systematic synthesis of knowledge-driven engineering, real-time data analytics, and perception-based inspection within brownfield SME constraints. Theoretically, the primary innovation is the synchronization of the Product Evaluation Matrix with high-fidelity Digital Twin validation models, creating an empirical control loop where cycle-time breakdowns directly trigger physical and logical system modifications. This replaces subjective planning loops with a data-driven decision-support mechanism. Furthermore, the research contributes to industrial data science by defining an edge-level data verification framework. This validation logic filters raw sensor signals based on the active program step, ensuring data fidelity before the information is sent to the production monitoring panels. Additionally, the thesis establishes a direct connection between modular hardware adaptations, such as 3D-printed fixture inserts, and the system's software control structure. This combined approach provides a systematic framework for upgrading legacy robot cells into functional cyber-physical production systems.

To support I5.0 principles, this methodology focuses on human-centric integration rather than replacing human labour. The implementation of simplified modular programming and visual interfaces is designed to lower technical barriers, supporting a transition where shop-floor operators could manage routine robotic cell reconfigurations with a reduced reliance on specialized coding expertise. Process transparency is maintained through real-time display panels and audio subroutines that provide continuous operational feedback. Finally, repetitive and force-intensive tasks are assigned to the robot under strict ISO 10218:2023 safety standards, while the operator handles complex problem-solving. This division of labour directly improves ergonomic safety and preserves manufacturing flexibility.

In summary, the synthesis of these methodological frameworks and empirical validations provides a robust, actionable blueprint for SMEs to sustainably modernize their legacy production infrastructure. Ultimately, this dissertation demonstrates that industrial resilience and human-centric automation can be achieved within resource-constrained brownfield environments without requiring prohibitive capital investments.

5.1 Discussion and Limitations

Experimental validation confirms that the developed methodology enables the low-cost reconfiguration of legacy equipment. The 23% throughput increase achieved in the simulation model indicates that real-time monitoring of operation cycle time components allows for the identification and elimination of production bottlenecks. However, it is crucial to acknowledge that this capacity gain was established within a simulation environment; physical realization across diverse production setups requires further validation.

Furthermore, the empirical validation of this methodology is constrained by its execution within only two partnering SMEs (Alise Technic and Comodule). This two-company scope limits the immediate generalizability of the framework across broader industrial sectors. Regarding the machine vision subsystem, the deployed setup relies strictly on rule- and threshold-based logic. While no escapes were observed within the tested sample of 350 products, that sample was drawn from normal production and did not contain a controlled number of seeded defects, so it does not support a quantified detection rate. The primary limitations of this validation are therefore the absence of a defect-characterised sample and the constrained size of the reference database. Although approximately 8% of conforming units were rejected due to ambient daylight

fluctuations, establishing a strictly controlled illumination environment is an elementary industrial prerequisite for 2D vision systems rather than a novel limitation of the proposed methodology. The true methodological constraint lies in the dataset size; establishing statistically robust reliability and a higher detection rate requires a significantly expanded image database and larger sampling sizes. Furthermore, as the validation partner (Comodule) has ceased operations, replicating this exact experimental setup to gather a larger dataset is no longer feasible, reinforcing the status of this implementation as a single-setup proof of concept.

As a secondary constraint, the data acquisition validation logic (Svalid) successfully filters electrical noise and ensures data accuracy, but the processing overhead introduces a measurable latency boundary when handling high-frequency data streams. Consequently, data exchange protocols require further optimization before applying this methodology to ultra-high-speed production lines.

Finally, regarding the digital twin integration, the system was validated as a predictive advisory environment utilizing a one-way data feed from the Dimusa platform. Consequently, true real-time bidirectional synchronization (Research Gap 2) remains partially unresolved within the strict constraints of brownfield legacy hardware, serving as a critical focus for future research.

5.2 Further Research

While this dissertation establishes a validated methodology for retrofitting and reconfiguring legacy robotic cells, several critical avenues remain for future research to expand the system's capabilities. The next evolutionary phase involves streamlining the initial configuration and mapping stages of the proposed knowledge-driven design framework. Specifically, ML models could be explored to process complex input datasets, including product geometries and localized legacy equipment capabilities. Rather than fully autonomous generation, these predictive models would aim to provide advanced decision-support, assisting engineers in selecting optimal adaptive end-effectors, smart fixtures, and robot configurations tailored to a specific product family.

Furthermore, future iterations of the framework could incorporate algorithmic analysis to highlight potential critical areas – such as physical cycle-time bottlenecks, high-risk human-robot proximity zones, and communication latency risks – before the virtual validation stage within the Digital Twin begins. To address the environmental sensitivity observed in the current rule-based vision system, future work will explore the application of machine learning for defect classification. The existing TTK UAS Learning Factory setup provides a practical environment to collect the diverse image datasets required for training such models. Transitioning from threshold-based logic to ML-assisted image analysis could potentially reduce the false-reject rate caused by variable lighting, thereby improving the system's overall robustness for high-mix production.

Ultimately, future inquiry will focus on advancing the Digital Twin architecture from a one-way predictive advisory tool toward true bidirectional real-time synchronization. Solving this communication latency will allow the methodology to scale from single-workstation reconfigurations to multi-cell factory networks. Additionally, the continued utilization of the TTK UAS Learning Factory will serve as a critical educational testbed, focusing on human-centric training frameworks to ensure that SME operators possess the necessary skills to independently manage and adapt these agile, cyber-physical modernization strategies.

The viability of scaling this reconfiguration methodology is actively being demonstrated at the TTK UAS Learning Factory (Publication V), commissioned in the autumn of 2024. This ongoing development is synergistically integrated with the research outcomes of Kristo Vaher's 2025 thesis, Reconfigurable Manufacturing Based on Autonomously Moving Collaborative Robot Solutions, defended at TalTech. By merging the stationary cyber-physical reconfiguration logic proposed in the current work with autonomously moving collaborative platforms, the scientific and methodological frameworks of both theses are being jointly advanced at TTK UAS. Supported by ASTRA+ funding, this facility networks legacy CNC machinery through a universal communication layer while successfully integrating these greenfield mobile assets. A primary objective of this joint project phase is to enable a single mobile robotic platform to reliably tend multiple legacy workstations, thereby maximizing overall equipment utilization across the shop floor.

As an educational and research testbed, the facility provides concrete, data-driven outputs. To date, the laboratory framework has facilitated one completed applied research thesis, with three additional theses currently in progress. Furthermore, the methodology will be piloted through prototype manufacturing for the FS Team Tallinn student formula team. The operational metrics gathered from this dynamic prototyping phase will directly validate the system's flexibility, serving as a critical stepping stone toward deploying these cyber-physical modernization strategies into full-scale industrial pilot applications.

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References

Babulak, E., & Wang, M. (2010). Discrete event simulation. *Aitor Goti (Hg.): Discrete Event Simulations. Rijeka, Kroatien: Sciyo*, 1.

Batth, R. S., Nayyar, A., & Nagpal, A. (2018). Internet of Robotic Things: Driving Intelligent Robotics of Future - Concept, Architecture, Applications and Technologies.

Benkamoun, N., ElMaraghy, W., Huyet, A.-L., & Kouiss, K. (2014). Architecture framework for manufacturing system design. *Procedia CIRP*, *17*, 88–93.

Berman, B. (2012). 3-D printing: The new industrial revolution. *Business Horizons*, *55*(2), 155–162. https://doi.org/10.1016/j.bushor.2011.11.003

Birglen, L. (2019). Design of a partially-coupled self-adaptive robotic finger optimized for collaborative robots. *Autonomous Robots*, *43*(2), 523–538.

Birglen, L., & Schlicht, T. (2018). A statistical review of industrial robotic grippers. *Robotics and Computer-Integrated Manufacturing*, *49*, 88–97. https://doi.org/10.1016/j.rcim.2017.05.007

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., & Wirth, R. (1999). The CRISP-DM user guide. 4th CRISP-DM SIG Workshop in Brussels in March,

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., & Wirth, R. (2000). CRISP-DM 1.0: Step-by-step data mining guide. *SPSS inc*, *9*(13), 1–73.

Collin, J., & Saarelainen, A. (2016). *Teollinen Internet*. Talentum.

Eiskop, T., Snatkin, A., & Karjust, K. (2017). Production monitoring system with predictive functionality. *J. Eng. Sci. Technol*, *12*(9), 2410–2425.

El Zaatari, S., Marei, M., Li, W., & Usman, Z. (2019). Cobot programming for collaborative industrial tasks: An overview. *Robotics and Autonomous Systems*, *116*, 162–180. https://doi.org/10.1016/j.robot.2019.03.003

Etz, D., Brantner, H., & Kastner, W. (2020). Smart manufacturing retrofit for brownfield systems. *Procedia Manufacturing*, *42*, 327–332.

Eurofound & Cedefop. (2020). *European Company Survey 2019: Workplace practices unlocking employee potential*. Publications Office of the European Union. https://www.eurofound.europa.eu/en/publications/all/european-company-survey-2019-workplace-practices-unlocking-employee-potential

European Commission. (2020). *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: An SME Strategy for a sustainable and digital Europe*. Brussels: European Commission Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0103

European Commission. (2025). *Annual Report on European SMEs 2024/2025: SME Performance Review*. https://webgate.ec.europa.eu/circabc-ewpp/d/d/workspace/SpacesStore/cc93d53c-13f1-41b7-b188-81f2b0e208cf/download

Eurostat. (2025). *Artificial intelligence by size class of enterprise* https://doi.org/10.2908/ISOC_EB_AI

Groggert, S., Elser, H., Ngo, Q. H., & Schmitt, R. H. (2018). Scenario-based manufacturing data analytics with the example of order tracing through BLE-beacons. *Procedia Manufacturing*, *24*, 243–249.

Gualtieri, L., Rauch, E., Vidoni, R., & Matt, D. T. (2019). An evaluation methodology for the conversion of manual assembly systems into human-robot collaborative

workcells. *Procedia Manufacturing*, *38*, 358–366. https://doi.org/10.1016/j.promfg.2020.01.046

Guerreiro, B. V., Lins, R. G., Sun, J., & Schmitt, R. (2017). Definition of smart retrofitting: First steps for a company to deploy aspects of industry 4.0. In *Advances in manufacturing* (pp. 161–170). Springer.

Heydaryan, S., Suaza Bedolla, J., & Belingardi, G. (2018). Safety Design and Development of a Human-Robot Collaboration Assembly Process in the Automotive Industry. *Applied Sciences*, *8*(3), 344. https://doi.org/10.3390/app8030344

Huang, B., Ma, S., Wang, P., Wang, H., Yang, J., Guo, X., Zhang, W., & Wang, H. (2018). Research and implementation of machine vision technologies for empty bottle inspection systems. *Engineering Science and Technology, an International Journal*, *21*(1), 159–169. https://doi.org/10.1016/j.jestch.2018.01.004

International Federation of Robotics. (2026). *Standardization*. International Federation of Robotics. Retrieved 17.02 from https://ifr.org/standardisation

International Society of Automation. (2021). *ANSI / ISA-95.00-xx. Enterprise Control System Integration*. Retrieved 07.01 from cANSI / ISA-95.00-xx. Enterprise Control System Integration

Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. *Journal of Industrial Integration and Management*, *7*(01), 83–111.

Jonsson, P., & Lesshammar, M. (1999). Evaluation and improvement of manufacturing performance measurement systems-the role of OEE. *International Journal of Operations & Production Management*, *19*(1), 55–78.

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.

Kalimuthu, M., Hayat, A. A., Elara, M. R., & Wood, K. L. (2021). Transformation Design Principles as Enablers for Designing Reconfigurable Robots.

Kangru, T., Mahmood, K., Otto, T., Moor, M., & Riives, J. (2020). Knowledge-Driven Based Performance Analysis of Robotic Manufacturing Cell for Design Improvement. ASME International Mechanical Engineering Congress and Exposition,

Kangru, T., Riives, J., Otto, T., Kuts, V., & Moor, M. (2020). Optimisation of decision-making process in industrial robot selection. *Journal of Machine Engineering*. https://doi.org/10.36897/jme/117788

Kangru, T., Riives, J., Otto, T., Pohlak, M., & Mahmood, K. (2018). Intelligent Decision Making Approach for Performance Evaluation of a Robot-Based Manufacturing Cell.

Kibira, D., Brundage, M. P., Feng, S., & Morris, K. (2018). Procedure for selecting key performance indicators for sustainable manufacturing. *Journal of Manufacturing Science and Engineering*, *140*(1), 011005.

Kindness, D. (2025, 18.06.2025). *Enterprise Resource Planning (ERP): Meaning, Components, and Examples*. Retrieved 09.03 from https://www.investopedia.com/terms/e/erp.asp

Koren, Y. (2010). *The global manufacturing revolution: product-process-business integration and reconfigurable systems*. John Wiley & Sons.

Koren, Y., Gu, X., & Guo, W. (2018). Reconfigurable manufacturing systems: Principles, design, and future trends. *Frontiers of Mechanical Engineering*, *13*(2), 121–136.

Lakshminarayanan, N., Surendra Babu, K., Amin, S., Sulficker, A., & Nassar, M. N. A. (2020). Design optimization of robotic work cell layout in automotive industries. *IOP Conference Series: Materials Science and Engineering*, *993*(1), 012036. https://doi.org/10.1088/1757-899x/993/1/012036

Lee, E. A. (2008). Cyber physical systems: Design challenges. 2008 11th IEEE international symposium on object and component-oriented real-time distributed computing (ISORC),

Lins, T., & Oliveira, R. A. R. (2020). Cyber-physical production systems retrofitting in context of industry 4.0. *Computers & Industrial Engineering*, *139*, 106193.

Liu, Y., Peng, Y., Wang, B., Yao, S., & Liu, Z. (2017). Review on cyber-physical systems. *IEEE/CAA Journal of Automatica Sinica*, *4*(1), 27–40.

Lõun, K., Riives, J., & Otto, T. (2010, April 22− 24). *Framework for extended use of technological resources in the network of enterprises.* Proceedings of the 7th International DAAAM Baltic Conference "Industrial Engineering", Tallinn, Estonia.

Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of industrial information integration*, *6*, 1–10.

Lu, Y., Liu, C., Wang, K. I.-K., Huang, H., & Xu, X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing*, *61*, 101837.

Lydon, B. (2020). *ISA95 In the IoT & Digitalization Era*. Retrieved January 06 from https://www.automation.com/en-us/articles/2020/isa95-in-the-iot-digitalization-era

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).

Materna, Z., Kapinus, M., Beran, V., Smrž, P., & Zemčík, P. (2018). Interactive spatial augmented reality in collaborative robot programming: User experience evaluation. 2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN),

Matt, D., Modrák, V., & Zsifkovits, H. (2020). *Industry 4.0 for SMEs: Challenges, opportunities and requirements*. Springer.

Melicher, M., Šišmišová, D., Vachálek, J., & Belavý, C. (2019). A cyber-physical systems paper survey about the concept, architecture and challenges for the deployment within the concept of industry 4.0. *Vedecké Práce Materiálovotechnologickej Fakulty Slovenskej Technickej Univerzity v Bratislave so Sídlom v Trnave*, *27*(45), 49–54.

Menezes, B. C., Kelly, J. D., Leal, A. G., & Le Roux, G. C. (2019). Predictive, prescriptive and detective analytics for smart manufacturing in the information age. *IFAC-PapersOnLine*, *52*(1), 568–573.

Microsoft. (2022). *What is cloud computing*. Microsoft. Retrieved November 28 from https://azure.microsoft.com/en-us/resources/cloud-computing-dictionary/what-is-cloud-computing

Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., Sauer, O., Schuh, G., Sihn, W., & Ueda, K. (2016). Cyber-physical systems in manufacturing. *CIRP Annals*, *65*(2), 621–641.

Oberc, H., Prinz, C., Glogowski, P., Lemmerz, K., & Kuhlenkötter, B. (2019). Human robot interaction–learning how to integrate collaborative robots into manual assembly lines. *Procedia Manufacturing*, *31*, 26–31.

Omron Corporation. (2021). *Photoelectric sensor E3F1-DP22*. Omron Corporation. Retrieved January 24 from

Onik, M. M. U., Kim, C.-S., & Yang, J. (2019). Personal data privacy challenges of the fourth industrial revolution. 2019 21st International Conference on Advanced Communication Technology (ICACT),

Paramasivam, V., & Senthil, V. (2009). Analysis and evaluation of product design through design aspects using digraph and matrix approach. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *3*(1), 13–23. https://doi.org/10.1007/s12008-009-0057-9

Razvi, S. S., Feng, S., Narayanan, A., Lee, Y.-T. T., & Witherell, P. (2019). A Review of Machine Learning Applications in Additive Manufacturing.

Saenz De Ugarte, B., Artiba, A., & Pellerin, R. (2009). Manufacturing execution system – a literature review. *Production Planning & Control*, *20*(6), 525–539. https://doi.org/10.1080/09537280902938613

Scholten, B., & Brandl, D. (2022). *The road to integration: A guide to applying the ISA-95 standard in manufacturing*. John Wiley & Sons.

Siemens Corporation. (2021). *RFID chip MDS D124*. Siemens Corporation. Retrieved January 24 from https://mall.industry.siemens.com/mall/en/WW/Catalog/Products/10047932

Singh, R., Mittal, M. L., Joshi, R., & Solanki, C. (2025, 2026//). Enhancing Circularity in SMEs by Incorporating Industry 4.0 Technologies—An Analysis on Gaps and Barriers. Proceedings of the UNIfied Conference of DAMAS, IncoME VIII and TEPEN Conferences, Cham.

Snatkin, A., Karjust, K., Majak, J., Aruväli, T., & Eiskop, T. (2013). Real time production monitoring system in SME. *Estonian Journal of Engineering*, *19*(1).

Stojmenovic, I. (2014). Machine-to-Machine Communications With In-Network Data Aggregation, Processing, and Actuation for Large-Scale Cyber-Physical Systems. *IEEE Internet of Things Journal*, *1*(2), 122–128. https://doi.org/10.1109/jiot.2014.2311693

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. (2018). Digital twin in industry: State-of-the-art. *IEEE Transactions on industrial informatics*, *15*(4), 2405–2415.

Tran, T.-A., Ruppert, T., Eigner, G., & Abonyi, J. (2022). Retrofitting-based development of brownfield industry 4.0 and industry 5.0 solutions. *IEEE Access*, *10*, 64348–64374.

United Nations. (2019). *World Population Prospects 2019: Highlights (ST/ESA/SER.A/423)*. U. Nations. https://population.un.org/wpp/assets/Files/WPP2019_Highlights.pdf

Vaughn, A., Fernandes, P., & Shields, J. T. (2002). Manufacturing system design framework manual.

Villani, V., Pini, F., Leali, F., Secchi, C., & Fantuzzi, C. (2018). Survey on human-robot interaction for robot programming in industrial applications. *IFAC-PapersOnLine*, *51*(11), 66–71.

Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems*, *48*, 144–156. https://doi.org/https://doi.org/10.1016/j.jmsy.2018.01.003

Want, R. (2006). An Introduction to RFID Technology. *IEEE Pervasive Computing*, *5*(1), 25–33. https://doi.org/10.1109/mprv.2006.2

Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23–45. https://doi.org/10.1080/21693277.2016.1192517

Xiong, G., Ding, Y., & Zhu, L. (2019). Stiffness-based pose optimization of an industrial robot for five-axis milling. *Robotics and Computer-Integrated Manufacturing*, *55*, 19–28.

Yang, C., Shen, W., & Wang, X. (2018). The internet of things in manufacturing: Key issues and potential applications. *IEEE Systems, Man, and Cybernetics Magazine*, *4*(1), 6–15.

Yim, M., Duff, D. G., & Roufas, K. D. (2000). PolyBot: a modular reconfigurable robot.

Zhang, Y.-J., Liu, L., Huang, N., Radwin, R., & Li, J. (2021). From Manual Operation to Collaborative Robot Assembly: An Integrated Model of Productivity and Ergonomic Performance. *IEEE Robotics and Automation Letters*, *6*(2), 895–902. https://doi.org/10.1109/lra.2021.3052427

Zhong, R. Y., Xu, X., Klotz, E., & Newman, S. T. (2017). Intelligent manufacturing in the context of industry 4.0: a review. *Engineering*, *3*(5), 616–630.

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Abstract

A Methodology for Designing Reconfigurable and Integrated Robotic Systems

Small and Medium-sized Enterprises constitute the backbone of the European industrial economy, yet their transition toward Industry 5.0 is systemically hindered by a reliance on rigid legacy robotic systems. To address these limitations, this dissertation establishes a comprehensive, knowledge-driven design methodology tailored for transforming brownfield manufacturing setups into flexible, cyber-physical production units. To achieve this objective, five core research tasks were executed:

1. Establishing a modular cyber-physical system architecture for legacy hardware.
2. Implementing a real-time data collection framework.
3. Developing a systematic reconfiguration methodology using a Product Evaluation Matrix.
4. Deploying automated machine vision features and safety structures for Human-Robot Collaboration.
5. Validating system performance through empirical use-cases.

The core methodological contribution formalizes a PEM synchronized with Digital Twin frameworks, establishing a predictive environment for virtual validation that reduces changeover downtime in HMLV production. Furthermore, the research defines an empirical control logic where real-time shop-floor metrics – specifically operation cycle time and OEE – serve as dynamic triggers for semi-autonomous system reconfigurations. The integrated methodology, including rule-based vision features and safety protocols, was experimentally validated through a CBQC use-case under the harmonized ISO 10218:2023 standards. Testing on a 350-unit production sample demonstrated the fail-safe behaviour of the inspection gate, which defaults to rejection when a feature cannot be verified; establishing a quantified detection rate requires a sample with a known defect count. The results demonstrate the feasibility of achieving industrial resilience, data interoperability, and safe HRC in resource-constrained manufacturing environments, establishing a foundational framework that necessitates further large-scale industrial testing.

Lühikokkuvõte

Ümberseadistatavate ja integreeritud robotsüsteemide arenduse metoodika

Väikesed ja keskmise suurusega ettevõtted (VKE-d) moodustavad Euroopa tööstusmajanduse selgroo, kuid nende üleminekut Tööstus 5.0 suunas takistab süsteemselt sõltuvus jäikadest pärandsüsteemidest. Käesolev doktoritöö lahendab need kitsaskohad, arendades tervikliku teadmispõhise rekonfigureerimismetoodika olemasolevate tööstuskeskkondade (brownfield) ümberkujundamiseks paindlikeks küberfüüsilisteks tootmisüksusteks. Püstitatud eesmärgi saavutamiseks täideti viis põhilist uurimisülesannet:

1. loodi modulaarne küberfüüsilise süsteemi (CPS) arhitektuur pärandseadmetele.
2. juurutati reaalajaline andmekogumise raamistik.
3. töötati välja süsteemne rekonfigureerimismetoodika, kasutades toote hindamismaatriksit (PEM).
4. integreeriti reeglipõhise masinnägemise tajukomponendid ja ohutusstruktuurid inimese-roboti koostööks (HRC).
5. valideeriti süsteemi toimivust empiiriliste kasutusjuhtude kaudu.

Uurimistöö peamine teaduslik uudsus seisneb PEM-maatriksi ja digitaalse kaksiku (DT) raamistiku sünkroniseerimises, mis loob empiirilise juhtimisloogika, kus reaalajalised mõõdikud – eriti tsükliandmed ja seadmete üldine efektiivsus (OEE) – toimivad dünaamiliste päästikutena poolautomaatse rekonfigureerimise algatamiseks suure varieeruvusega väikesemahulises (HMLV) tootmises. Praktiline uudsus seisneb madala maksumusega avatud sidestandarditel põhinevas moderniseerimisarhitektuuris, mis integreerib masinnägemise ja nutikad lisaseadmed vastavalt harmoneeritud ISO 10218:2023 ohutusstandarditele, mida valideeriti koostöörobotil põhineva kvaliteedi-kontrolli (CBQC) rakenduses. Eksperimentaalne katsetamine 350-tootelises valimis kinnitas kontrolliloogika konservatiivsust ehk tunnuse mittevastamisel suunatakse toode praaki, kuid tuvastusmäära arvuline hindamine eeldab teadaoleva defektide arvuga valimit. Hariduslik uudsus toob sisse inimkesksed koolitusraamistikud, mis võimaldavad olemasoleval tööjõul nutikaid automatiseeritud keskkondi iseseisvalt seadistada ja hooldada. Töö tulemused toimivad kontseptsiooni tõestusena (proof-of-concept), viidates, et tööstuslikku paindlikkust, andmete koostalitlusvõimet ja ohutut inimese-roboti koostööd on teostatav juurutada piiratud ressurssidega tootmiskeskkondades ilma suurte alginvesteeringuteta. Samas eeldab täiemahuline tööstuslik rakendamine edasist laiaulatuslikku valideerimist.

Appendix 1

Publication I

Moor, M.; Vaher, K.; Riives, J.; Kangru, T.; Otto, T. (2021). Modern Robot Integrated Manufacturing Cell According to the Needs of Industry 4.0. Proceedings of the Estonian Academy of Sciences, 70 (4), 407−412. DOI: 10.3176/proc.2021.4.06.

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MANUFACTURING
ENGINEERING

Modern robot-integrated manufacturing cell according to the needs of Industry 4.0

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Abstract. The continuous need to develop Industry 4.0 branches has led to a position where highly sophisticated and multi-layer smart robotic systems are guiding the way to future manufacturing. This study aims to build a connectivity and system intelligent layer on top of a co-bot integrated Computer Numerical Control (CNC) based manufacturing cell. The connectivity layer is used to bypass all the data collected from machines to the upper intelligent layer and vice versa. When raw data arrives in the intelligent layer, it will be converted to information and again to knowledge for reflection to be sent back to the cell. Machine-to-Machine Communication and Digital Twin process for optimization are used for data conversions. This study is a downscale example of the Cyber-Physical System (CPS) for further development of the existing robot cells.

Key words: Industry 4.0, industrial robot, co-bot, modern manufacturing.

1. INTRODUCTION

The combination of technologies, such as Smart Sensors, Internet of Things (IoT) [1], Machine-to-Machine Communication (M2M) [2], and Artificial Intelligence (AI) based solutions have fundamental importance in the process of further development of the existing manufacturing cells. The next phase for production units in the future is to implement the data collecting level as criteria for decision-making possibilities for the existing robot cells. This can be achieved by using virtual environments for data processing and management of the actual robot cell. In this article, possible solutions and methods are investigated for upgrading the existing production cells to the level of automation and intelligence needed for Industry 4.0 (I4.0).

The goal was to define possibilities of how to develop the existing production system to meet the needs of I4.0 principles by applying Smart Sensor technology. The information was collected, processed, and controlled by the Manufacturing Execution System (MES) [3] to ensure continuous workflow in every production unit as a whole system.

2. ONTOLOGY OF MODERN MANUFACTURING

Knowledge-based economy and production is characterized by continuously shortening product life cycles, but continuously increasing demands towards products' functionality, quality, and other customers' requirements. The orientation towards development and improvement of the production system and its efficient use is extremely important. A company is an entire system that operates in a certain location and customer-oriented field of activity. A company may belong to a group or network, whereby its belonging to the network may be either abstract or having certain connections or functions with the network [4].

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The production system has certain resources, processes, and strategies (Fig. 1). The production system is characterized by the physical environment (number, type, layout, and location) and functional environment that is expressed by technological possibilities of machine tools. Machine tools have mutual logistical relations inside the system as well as relations with the external environment. Technological possibilities of a company's production system evolve mainly based on machinery (CNC tools, Industrial Robots (IRs) and Co-bots, presses, welding equipment, etc.). Technological possibilities can be defined as a set of characteristics of the current device for producing a specified workpiece or performing a certain technological task.

The industrial production of the future will be characterized by strong individualization of products under the conditions of highly flexible production, extensive integration of customers and business partners in value-added processes. Future manufacturing combines technology, knowledge, information, and human ingenuity to develop and apply manufacturing intelligence. It comprises the smart use of networked information for demand-dynamic economics such as: integrated enterprise and supply chain as well as broad-based workforce engagement; industrial robots that work safely with people in shared spaces; and metal-based additive manufacturing. Driven by the software connected to the Internet, the real and virtual worlds are growing closer and closer together to form the IoT.

In this article, we focus mainly on the workplace level, by which we mean a robotic workplace, and view it as an integration of different hardware and software tools forming a Cyber-Physical System (CPS) (Fig. 2). CPS is based on a multi-dimensional complex space that generates and evolves diverse subspaces to contain different types of individuals interacting with, reflecting, or influencing each other directly or through the cyber physical subspace. CPSs are engineered systems that are built from and depend upon the synergy of computational and physical components.

Three main functionalities for modern robot-cells are:

- Internet of Things,
- Machine-to-Machine Communication,
- Big Data.

IoT gives the possibility to connect more devices to a central controller. This setup allows manufacturers to gather more data, also to streamline and digitize their processes more efficiently. With M2M the success of data exchange and autonomous automation would be achieved, and it depends on the machines' ability to communicate and their real-time responses with one another. The role of data and information is currently increasing in manufacturing. The extended supply chain, as well as horizontal and vertical value streams are based on data exchange and information processing. Thanks to IoT, data transfer possibilities, data analytics, different decision-making algorithms, AI possibilities can be used in the workplace for intelligent manufacturing with adaptive control, agile planning and real-time management.

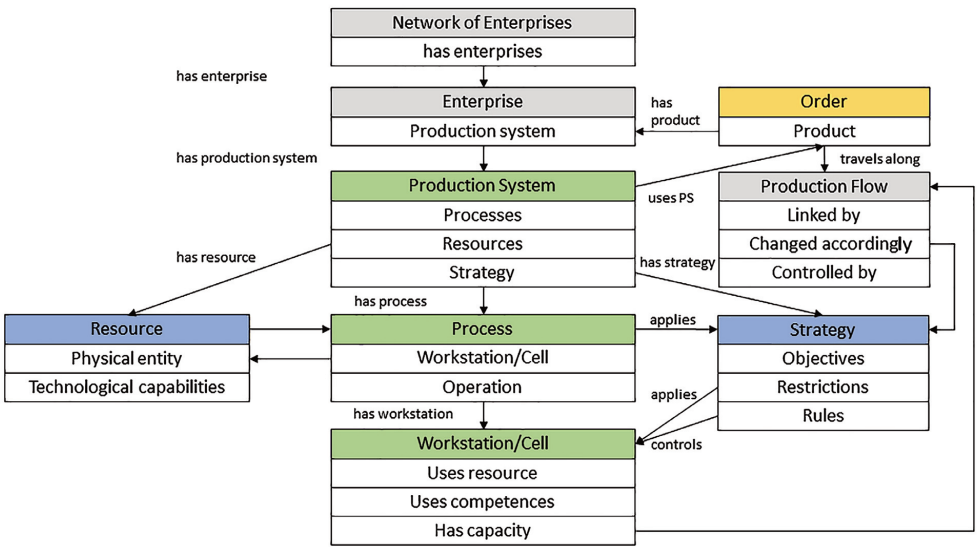


Fig. 1. Ontology in manufacturing [4]. PS − Production System.

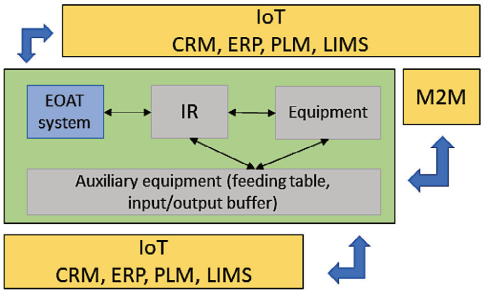


Fig. 2. Robot cell with CPS functionality. CRM – Customer Relations Management; ERP – Enterprise Resource Planning; PLM – Product Lifecycle Management; LIMS – Laboratory Information Management System; EOAT – End-of-Arm Tooling.

3. INTEGRATION AND CONNECTIVITY

The new manufacturing architecture follows the need to integrate vertical and horizontal value chains. As the production is becoming more intensive, more digital solutions (ERP, PLM, MES, CAD/CAM/CAQ, etc.) in both value chains are implemented into the general computing architecture trends. Over time smaller computers and PCs have distributed functions over networks, and distributed computing has been refined in many ways with Service Oriented Architecture, HTTP, Remote Procedure Call (RPC), and other functions.

This integration and connectivity are formalized with the ISA-95.00-xx standard [5]. Traditionally, ISA-95 has been implemented in a 5-layer system network architecture, implying that each level only communicates through adjacent levels (Fig. 3). This implementation was built around the technology available at the time it was conceived, which has changed significantly with high power computers, high-performance networking, and embedded edge computing, all supported by more sophisticated and refined software that has been developed for general computing [6].

The technical innovation of Industry 4.0 towards smart manufacturing is characterized by the integration of manufacturing systems, using digital twin principles in the different value chain positions, virtual reality and augmented reality in designing and execution stages, big data, and data analytics for continuous improvement.

4. INTEGRATED MANUFACTURING IMPLEMENTATION

In this article, we have focused on the implementation of miniature production system which has been under development at TTK University of Applied Sciences (Fig. 4). The equipment and component description was explained

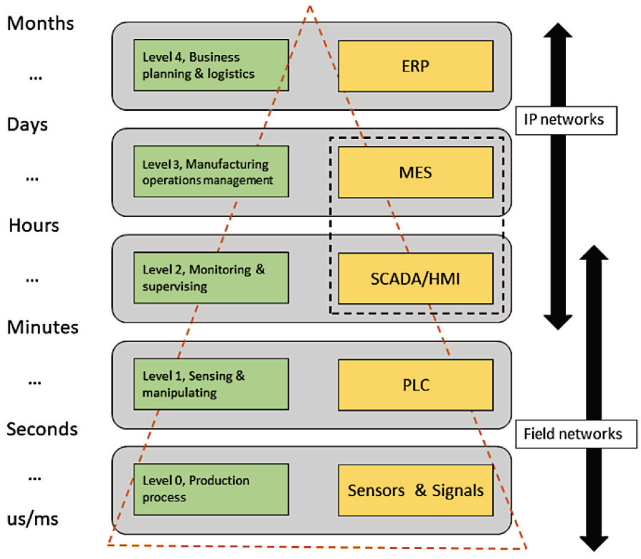


Fig. 3. Integration and connectivity in manufacturing according to ISA-95.00 [6]. SCADA – System Control and Data Acquisition; HMI – Human-Machine Interface; PLC – Product Life Cycle.

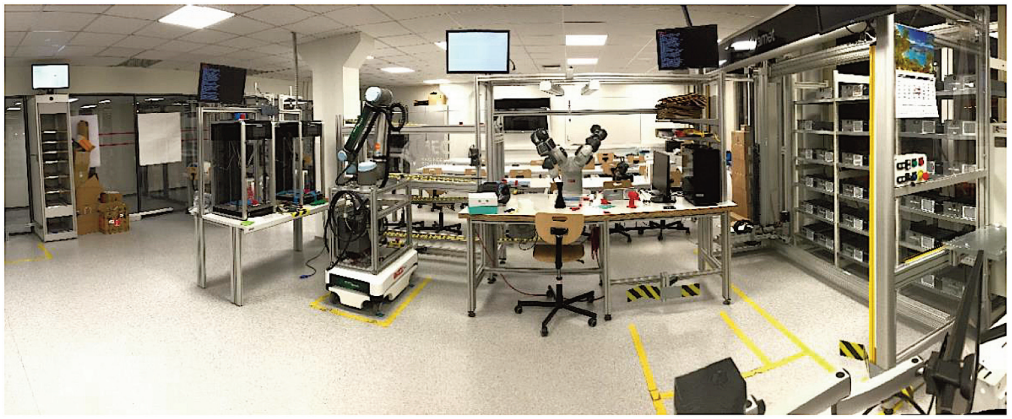


Fig. 4. TTK Industry 4.0 CPS.

in [7], and the multi-layer CPS implements similar ontology of manufacturing as stated above (Fig. 1).

The entire system works autonomously, where incoming orders are planned in the ERP system, M2M communication and the sequence of production operations is managed by a program created at the MES level. All devices in the system are connected to MES via LAN or Wi-Fi but are independent of each other and do not require constant communication with a higher-level program (Fig. 5). All the units are programmed for each operation, and the MES program distributes only start commands and waits for execution confirmation to distribute new commands. Error reports from devices are forwarded to MES where necessary decisions are made for further operations. According to

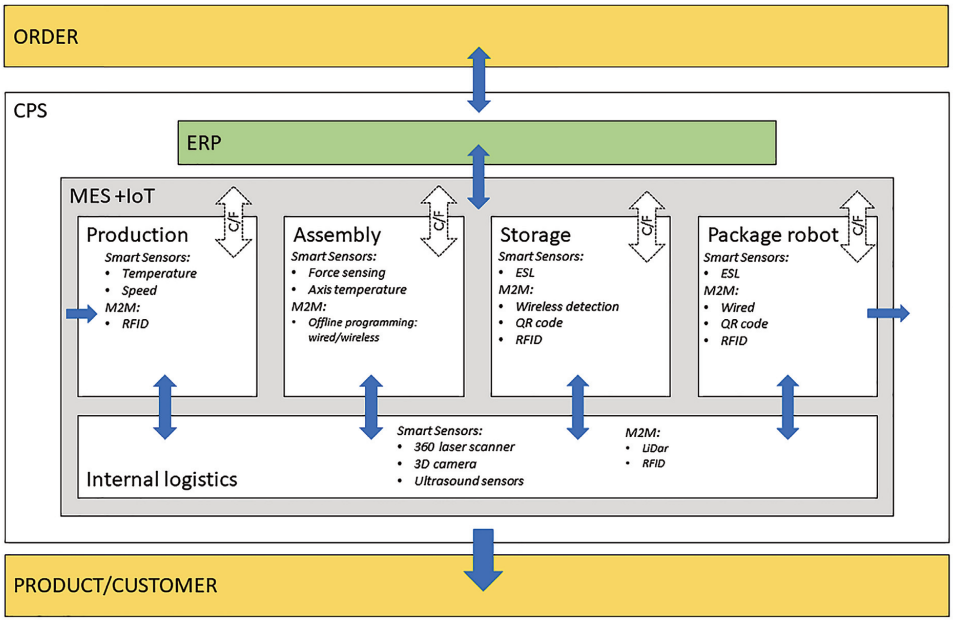


Fig. 5. Developed system's schematic diagram. ESL – Electronic Shelf Label; RFID – Radio Frequency Identification.

the number of details needed to produce, MES is capable of evaluating unused workstations and decide how to produce similar items or details in parallel.

The system design is flexible and easy to reconfigure according to I4.0 principles, with the possibility to add new production equipment to the entire system without the need to make major changes to the control system. The mobile robot arm plays a major role in this factory, which enables to apply a similar method in the existing factory without making major adjustments for the robots. Each unit is equipped with photoelectric sensors (PNP output) [8] to monitor and give feedback about the current situation at the workplace − first of all to PLC and then to MES for the management of other units. Another important part of CPS is RFID technology [9] with the RFID chip [10], reader [11], communication module, and power module. Each production plate and storage box are equipped with an RFID chip and every unit, including MES, has live information.

5. CONCLUSIONS

Modern manufacturing has been changing rapidly in the last decade. The sophisticated and multi-layered robot-integrated manufacturing is not in distant future. Our entrepreneurs have the machinery and equipment to manufacture products according to the customer needs, but the continuously shortening product life cycle and the product's increasing complexity forces us to raise the efficiency of the existing system. In this paper, we have reviewed the possibilities of applying I4.0 principles to the existing downscaled IR and co-bot based manufacturing system, by using Smart Sensors and M2M connectivity combined with IoT based manufacturing software. Our study indicates that the usage of I4.0 technologies is strictly based on the needs, and the purpose is to raise the efficiency of certain robot-based manufacturing cells.

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REFERENCES

1. Batth, R. S., Nayyar, A. and Nagpal, A. Internet of robotic things: Driving intelligent robotics of future − concept, architecture, applications and technologies. In *Proceedings of the 2018 4th International Conference on Computing Sciences (ICCS), Jalandhar, India, August 30−31, 2018*. IEEE, 2019, 151−160. https://doi.org/10.1109/ICCS.2018.00033
2. Stojmenovic, I. Machine-to-Machine communications with in-network data aggregation, processing, and actuation for large-scale cyber-physical systems. *IEEE Internet Things J.*, 2014, **1**(2), 122−128. https://doi.org/10.1109/JIOT.2014.2311693
3. Saenz de Ugarte, B., Artiba, A. and Pellerin, R. Manufacturing execution system – a literature review. *Prod. Plan. Control*, 2009, **20**(6), 525−539. https://doi.org/10.1080/09537280902938613
4. Lõun, K., Riives, J. and Otto, T. Framework for extended use of technological resources in the network of enterprises. In *Proceedings of the 7th International DAAAM Baltic Conference "Industrial Engineering", Tallinn, Estonia, April 22−24, 2010.* TTU Press, 316−321.
5. ANSI/ISA-95.00-xx. Enterprise Control System Integration.
6. Lydon, B. (ed.). ISA-95 in the IoT and digitalization era. www.automation.com (accessed 2020-01-06).
7. Vaher, K., Vainola, V. and Otto, T. Industry 4.0 laboratory. Industry 4.0, technological basis of "Industy 4.0". In *1/5: Proceedings of the IV International Scientific Conference, Industry 4.0. Summer session, Burgas, Bulgaria, June 24−27, 2019*. Industry 4.0, Sofia, 52−53.
8. Omron Corporation. Photoelectric sensor E3F1-DP22. https://industrial.omron.eu/en/products/E3F1-DP22 (accessed 2021-01-24).
9. Want, R. An introduction to RFID technology. *IEEE Pervasive Comput.*, 2006, **5**(1), 25−33. https://doi.org/10.1109/MPRV.2006.2
10. Siemens Corporation. RFID chip MDS D124. https://mall.industry.siemens.com/mall/en/WW/Catalog/Products/10047932 (accessed 2021-01-24).
11. Siemens Corporation. RFID reader RF340R (GEN2). https://support.industry.siemens.com/cs/pd/467302?pdti=pi&dl=en&lc=en-GB (accessed 2021-01-24).

Tööstus 4.0 printsiipidel põhinev moodne ja integreeritud tootmisjaoskond

Madis Moor, Kristo Vaher, Jüri Riives, Tavo Kangru ja Tauno Otto

Tehnoloogia areng koos Tööstus 4.0 printsiipidega on suunanud meid olukorda, kus kõrgelt arenenud ja mitmekihilised intelligentsed robotsüsteemid näitavad teed tulevikku. Artiklis on välja toodud, kuidas arendada ühilduvust eri üksuste vahel. Tootmisüksus põhineb TTK Tööstus 4.0 labori baasil ja tööstusrobotite, koostöörobotite ja CNC-seadmete baasil ning seadmete omavaheline infojagamise mudel on eeskujuks tööstuslike rakenduste arendamisel. Ühilduvuse kiht süsteemis on vajalik info kogumiseks eri üksustelt, info töötlemiseks ja otsuste vastuvõtmiseks. Selle tarbeks on vajalik kasutada kombinatsiooni eri tehnoloogiatest, nagu targad sensorid, asjade internet (IoT) ja masinatevaheline suhtlus (M2M), mis tagab kiire infoedastamise ning andmete optimeerimisvõimalused. Uuringu tulemustest selgub, et Tööstus 4.0 printsiipidel põhinev moodne tootmisjaoskond on tugevalt seotud vajaduste ja eesmärkidega, et tõsta olemasoleva robottootmise efektiivsust.

Appendix 2

Publication II

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: 10.1063/5.018950

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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].

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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.

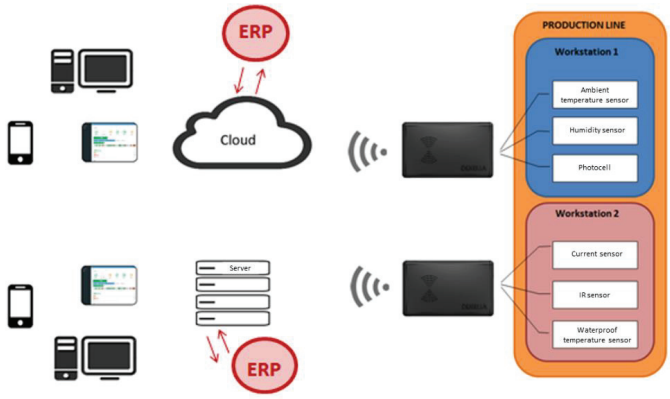


Figure 1 The principal scheme of Dimusa system

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

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

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- 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.

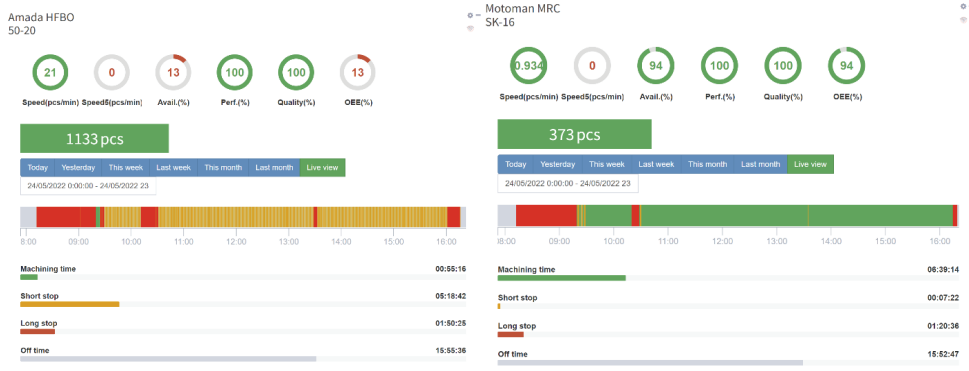


Figure 2 Dimusa monitoring panel

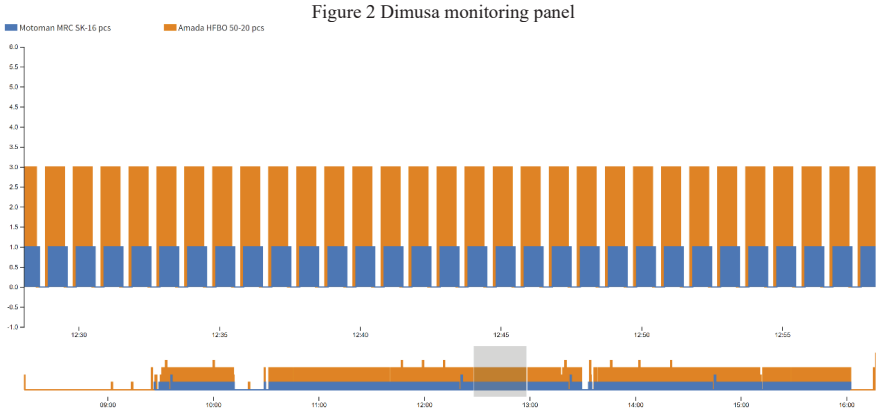


Figure 3 Example of Amada CNC bending machine sensor activities

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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.

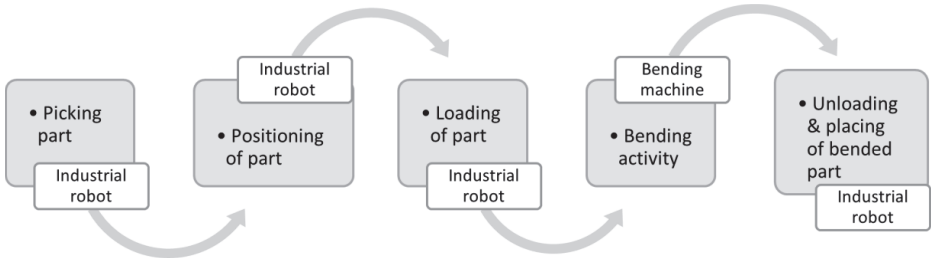


Figure 4 Process flow of robot bending cell

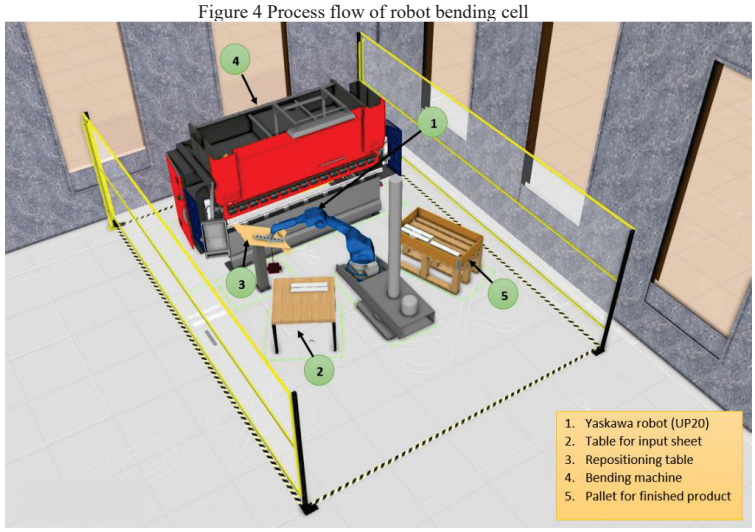


Figure 5 Virtual simulation model of bending cell in 3D environment

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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/

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Appendix 3

Publication III

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AI functionality,
collaborative robot,
machine vision,
adaptive grippers

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AI FUNCTIONALITIES IN COBOT-BASED MANUFACTURING FOR PERFORMANCE IMPROVEMENT IN QUALITY CONTROL APPLICATION

Modern manufacturing faces vastly changing challenges. The current economic situation and technological developments in terms of Industry 4.0 (I4.0) and Industry 5.0 (I5.0) force enterprises to integrate new technologies for more efficient and higher-quality products. Artificial intelligence (AI) and Machine Learning (ML) are the technologies that make machines capable of making human-like decisions. In the long run, AI and ML can add a layer (functionality) to make IoT devices more interactive and user-friendly. These technologies are driven by data and ML uses different types of data for making decisions. Our research focuses on testing a cobot-based quality control (CBQC) system that uses smart fixture and machine vision (MV) to determine the cables inside products with similar designs, but different functionality. The products are IoT modules for small electric vehicles used for interface, connectivity, and GPS monitoring. Previous research describes the methodology of reconfiguration of existing cobot cells for quality control purposes. In this paper, we discuss the testing of the CBQC system, together with creating a pattern database, training the ML model, and adding a predictive model to avoid defects in product cable sequence. Preliminary testing is carried out in the laboratory environment which leads to production testing in SME manufacturing. Results, developments, and future work will be presented at the end of the paper.

1. INTRODUCTION

Robot solutions are widely used by small and medium-sized enterprises (SMEs) in every part of the world. SMEs aim to increase the quality of products and throughput, but moreover, reduce the lack of human labour. According to Eurofound, 39% of European manufacturing companies stated limitations in production due to labour shortages. According to the prediction, made by the United Nations analysis, we will witness a decrease of 95 million workers from 2015 to 2050 [1]. The decreasing trend and demographic effect will accelerate

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and force even more rapid usage of smart robotic systems. While industrial robots (IRs) are widely used in high-volume production and large enterprises, SMEs require high flexibility and multi-purpose application robot cells (RCs). For SMEs, a collaborative robot (cobot) is cost efficient and flexible solution which can help to solve the stated problems above. European manufacturing is represented by 98% of SMEs which mainly produce high-mix low–volume products [2], where the speed of retune and flexibility between different positions in production is essential. It is reasonable to implement and adapt parts of I4.0 [3] branches such as Internet of Things (IoT), Adaptive grippers [5], System Simulation, and Integrated Manufacturing [4]. A previous study was conducted by the authors of this article to develop a methodology to reconfigure an existing RC into a quality control system for SME production [6]. The objective of this research is to develop AI features for an existing RC to improve the performance of cobot-based quality control system.

To establish AI features in a RC, an interconnectivity level must be developed between different equipment inside the RC. The system consists of a cobot and its controller, adaptive gripper, smart fixture, and machine vision (MV) system. The information gathered from MV serves great importance in terms of digitalization and takes robot cells to the next level. A product-based database is essential to be developed for the decision-making module. This decision-making module consists of rules and constraints to detect and decide on the ongoing processes inside the robot cell. This study discusses an approach to enable AI features using variable programming methods, allowing quickly adapt changing products in SME production.

The rest of this paper is organized as follows. The second chapter presents the previous research done on similar topics. The third chapter describes the CBQC system communication. The fourth chapter presents the AI features of CBQC programming. The fifth chapter gives an overview of CBQC setup and testing. The final chapter concentrates on discussion and conclusions, followed by future work and acknowledgment.

2. LITERATURE REVIEW

2.1. COLLABORATIVE ROBOTS IN PRODUCTION

The use of cobots in the industry is constantly growing, growing by 31% in 2022 compared to the previous year, reaching a 10% global market share [7]. The main reason is their minimal installation cost into an existing non-robotised production process to perform repetitive tasks and a short user training period [8]. The RC can be characterized by the level of cooperation, where the low and high are as follows. Starting at the lowest, similar setup to a classic industrial robot cell layout, the robot is separated from the person and performs a given task. Cooperation at the highest level, the robot monitors human worker movements and contributes as needed. The implementation costs are corresponding; in the first case, it is possible to use existing “off–the–shelf” solutions, ensuring the minimum costs. On the other hand, in the case of a high level of cooperation, a specific approach to the production process is needed [9].

2.2. ADAPTIVE GRIPPER SYSTEMS

One of the important steps in implementing a collaborative robot in the SME production process is the selection of a tool or end effector. The benefit of the cobot is the ease of ability to be relocated as needed and used to perform various tasks. Depending on the production task change, the shape of the parts or tools that are likely to be gripped also changes, and it is no longer possible to use only one special jig. This, in turn, usually places more complex requirements on the end effector. Widespread grippers use 2 to 6 fingers to be controlled either with an electric, pneumatic, or hydraulic drive, as L. Birglen et al. presented in their review on IR grippers [10]. Kinematically, either parallel or radial gripping is widely used. Reconfigurable grippers have come into use, with the number of fingers, grip, range, geometry, and force being easily changed [5]. For the adaptive gripper systems, finger speed, acceleration, slippage and force/torque sensing and controlling are essential functions. B. Zhang et al. discussed different methods and strategies for grasp process control and condition monitoring in agricultural robots, where force/torque sensing is essential [11].

2.3. IOT MODULE AND TECHNOLOGY

With the widening application of AI functions in SME processes (decision-making, automation, determining and optimizing parameters, and operations), to reduce production costs and lead times, the need for information (capture, storage, retrieval, processing, and redirection to use) from different enterprise levels has increased considerably. IoT technology covers almost all those needs in a small, low-cost, modular form. IoT architecture comprises four main layers [12]: sensing or actuating, network, data processing, and application. All the layers can be built into the module, or when the module size and cost are important, only the first two layers are minimal. The International Data Corporation (IDC) predicts an annual growth rate of 11% for IoT devices, reaching $345 billion by 2027 [13].

2.3.1. IOT DEVICES FOR PRODUCTION MONITORING

Production monitoring is used to verify the process status and movement of units, materials, and products. Data from production cells or warehouses are gathered, prepared, and transmitted for future processing. Data can be collected from motion, position, environmental, or similar sensors. From the manufacturing point of view, Overall Equipment Effectiveness (OEE) or Overall Labor Effectiveness (OLE) are the most common Key Performance Indicators (KPI). To calculate those KPIs, states, speeds and units are measured and reported to the Manufacturing Execution System (MES) [14]. From MES, the data is converted to information, and further decisions or processes can be made.

2.3.2. IMPLEMENTATION IN THE LAST 5-10 YEARS

Online monitoring of production and the implementation of IoT devices are part of the bigger manufacturing digitalization process. Digitalization has grown significantly in the last

decade, reaching a point where there is a desire and will to innovate, but its implementation is significantly affected by the market's uncertainty. 31% of companies that have gone through the digitization process admit that they still collect data through a non-digital process. In addition, entrepreneurs are aware of the possibilities of MES, but 37% lack resources and 34% lack the budget to implement MES [15]. The current situation can also be seen as a momentary slowdown of rapid growth in preparation for the next sprint. Virtual reality, simulation, augmented reality, cyber-physical systems (CPS), artificial intelligence (AI), Internet of Things (IoT), Industrial Internet of Things (IIoT), cloud computing and big data are listed as key technologies of the future industry [16]. The research mentioned above supports the background for our study and using its elements, we have adapted AI functionalities for improving the performance in quality control applications.

3. CBQC SYSTEM COMMUNICATION

3.1. CBQC SYSTEM LAYOUT AND MODEL

For creating a better understanding of a CBQC system, a virtual model of the system is presented, see Fig. 1. We can separate four main areas of the system: input, process, output, and defective area. The process area consists of system equipment and is the most important part of the system. It consists of a cobot Omron TM5-900, adaptive gripper Robotiq 2F-140, MV Cognex In-Sight 7905C, and a smart fixture.

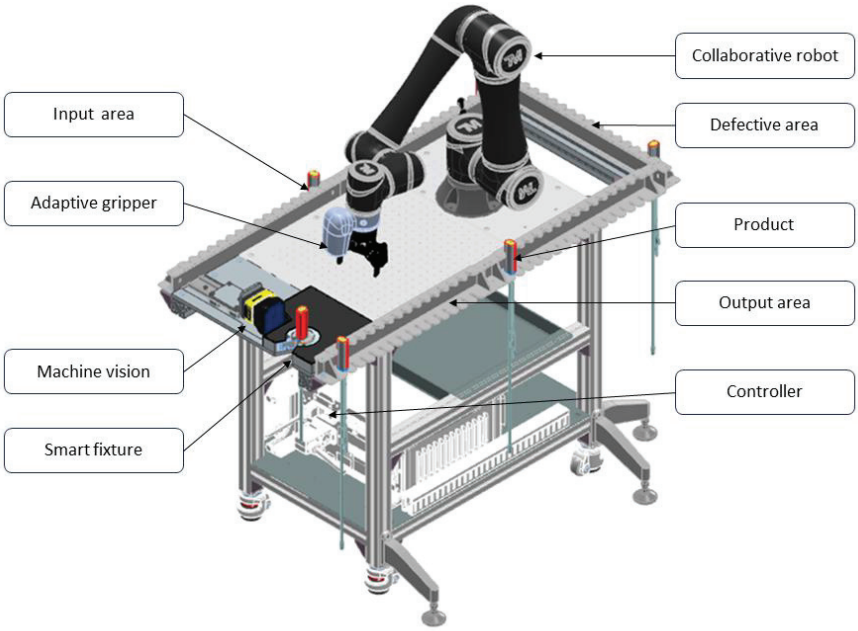


Fig 1. CBQC system areas

3.2. SYSTEM LIMITATIONS

The system developed is built on existing hardware and software available in the university and therefore has some limitations compared to automation system integrators. Additionally, for the hardware mentioned above, the software used for simulation and programming is the following: Omron TMFlow for cobot programming, RoboDK for initial simulation and layout design, Cognex In-Sight Explorer software for MV camera programming, ModPoll software for Modbus communication testing and evaluation.

For the communication between system components physical I/O (Input/Output) connections were used and Modbus communication was established between the MV camera and robot controller. Physical (I/O) connections between the system devices for communication (number of inputs and number of outputs and their functions) are shown in Table 1. For the robot controller, there are available 16 physical inputs and 16 physical outputs for communication with external devices. Also, different communication protocols (Modbus TCP/RTU, Ethernet TCP/IP, RS232, Profinet) are available.

Table 1. I/O values for cobot controller

Input nr	Function		Output nr	Function
DI 0	Sensor for rotational cylinder position 1 detection		DO 0	clockwise rotation of the product in front of the camera (position 1)
DI 1	Sensor for rotational cylinder position 2 detection		DO 1	Counter clockwise rotation of the product in front of the camera (position 2)
DI 2	reserved		DO 2	Selection of MV camera job (bit 1)
DI 3	reserved		DO 3	Selection of MV camera job (bit 2)
DI 4	reserved		DO 4	MV camera trigger. Gives a signal to the camera to take a picture.
DI 5	Reading the camera job result. If the job was OK, the result is 1, if NOK, the result is 0		DO 5	switching on compressed air for small cylinders for product gripping
DI 6	reserved		DO 6	reserved
DI 7	reserved		DO 7	reserved

3.3. SYSTEM INTEGRATION

The cobot, cobot controller, MV system and fixture are connected and integrated by considering mechanical constraints and by establishing communication between system components. Physical outputs are needed for controlling the solenoids for pneumatical cylinders (fixing the product, turning the product in front of the camera) and for sending signals (triggering, program number) to the MV camera. Physical inputs are for detecting the position of the product (cylinder positions 1 and 2) and for reading the signals (camera job result) from the MV camera. Modbus communication was used for reading cobot current position coordinates to calculate new program positions and for communication with the MV camera.

As system integration is a very complex task, the important steps are shown below to be taken to carry out a similar integration project efficiently. The steps are as follows:

1. selection and design of necessary system components (in our case SolidEdge);
2. simulation of the system by using a simulation environment (in our case RoboDK);
3. assembly and connection of system components mechanically, testing cobot reachability;
4. creation of the MV camera program by using suitable software (in our case Cognex In-Sight);
5. creation of the robot program taking into account modularity and parametric programming (in our case Omron TMFlow);
6. establishing physical connections (I/O) and communication between system components, testing the communication (in our case ModPoll, WireShark);
7. testing of the programs and communication to ensure correct functioning.

4. AI FEATURES OF A CBQC PROGRAMMING

4.1. COLLABORATIVE ROBOT PROGRAM STRUCTURE

In this study, the cobot program follows a certain workflow [17] and has been divided into different levels of programs: main, sub, and decision program, see Fig. 2. The main program serves as a master, having full control over subprograms. The structure follows a sequential routine with a set of rules and limitations. There is a limitation in the input area, where the number of products may vary from 15 to 45 products. Another rule is the check-up for adaptive gripper parametric status. Additionally, the force sensing available for the cobot can also be used to recognize collisions at the end-effector level [18]. Sub "2_0_Home" carries out force control and open range for the gripper but is only executed once in a cycle. This is achieved by decision module 2, located between tested products (ON/NOK) and the next loop of the cycle.

The motion movements are classified according to the location of the CBQC system layout to simplify and reduce the time consumption of necessary adjustments in motion parameters or the process itself. Preliminary programming may be more time-consuming than conceptional programming, but on the other hand, the concept allows to detection and repair of any issues which may influence the successful process execution. The schematic presentation of a program structure helps to understand the complexity of a program and focus on essential activities. In this study, the essential focusing points are on sub-programs: "Pick_up", "CAM_trigger", "Tested_OK", and "Tested_NOK", see Fig. 2.

In reality, the program layout is more linear, see Fig. 3, and the previous schematic structure is the base of the master program activities. Based on the relationships among robots, human operators, and processes, collaborative tasks can be classified into four categories [19]: independent, sequential, simultaneous, and supportive. Our study focuses on sequential collaboration where every program in the master program list is equipped with indirect functions such as „display" and „voice". These functions create a far better understanding between the operator and the CBQC system. The display function enables an option for monitoring the process on site (status of local and global variables) and offers the possibility to monitor these features online, using cloud technology. The Voice function offers an

informative overview to any operator near the CBQC system. Since the system is designed to production flow and stand between manual workplaces (EOL testing and glueing), productivity is affected by cooperation. Both productivity and ergonomic performance are of significant importance in manufacturing [20].

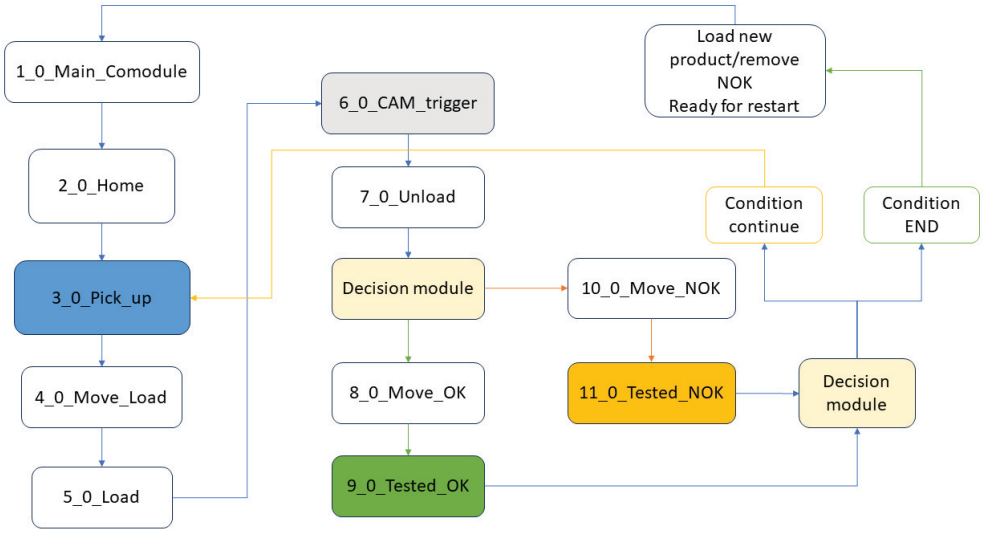


Fig 2 A schematic view of program structure

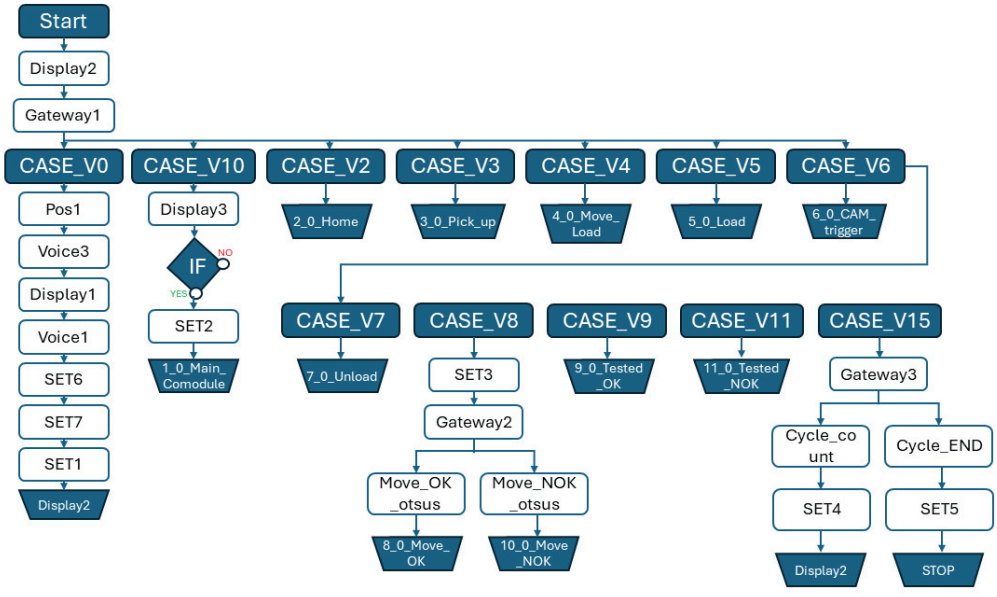


Fig. 3. An example of master program – Main_Comodule

4.2. LOGIC AND VARIABLES

A cobot program with different levels does not make the program shorter. It simplifies the program and ensures easy following. The logic of our research cobot program uses a different type of variable method: local variables, global variables, and Modbus protocol. Modbus is a request-response protocol implemented using a master-slave relationship. In a master-slave relationship, communication always occurs in pairs—one device must initiate a request and then wait for a response the initiating device (the master) is responsible for initiating every interaction [21]. Local variables function as though they were temporary attributes defined in a specific logic section which disappear when the logic section is finished executing. Local variables are useful for testing variables in loops and storing locally used, unique values for each entity at the current location [22]. A global variable, on the other hand, is declared outside any functions or tasks, and therefore typically appears at the very top of a program. Because they are declared at a level broader than any task or function, all functions and tasks can "see" global variables, and they do not lose their value even after a function or task ends [23].

In our study, we use Modbus protocol to read the present values of the cobot linear axis and the information is used for next motion calculations. For example, this logic is used in most local variables in combination with Modbus read and global variables. Modbus communication explanation is shown in Table 2.

Global variables have control over essential sub-programs stated above, see 4.1. In terms of the number of program motion positions, global variables allow for a decrease of motion steps over five times. We have used 66 variables all together throughout the 11 programs and this example is stated according to 15 products handled in the CBQC system. It is possible to increase the number of products to 45 without making any design changes to the system layout. An example of global variable functionality is shown in Table 3.

Table 2. Modbus communication

Definition	Address	Type	Explanation
Preset_tcp_y	7051	Float	Read current position value of Y axis
Preset_tcp_x	7037	Float	Read current position value of X axis
Preset_tcp_z	7041	Float	Read current position value of Z axis

Table 3. Example of global variables in CBQC system

Module	Name	Type	Value	Explanation
1_0_Main_Comodule	G_num3	Int	0	Main program - Case decision value – program structure logic
3_0_Pick_up	G_num1	Int	9	Input grip area – counts input product program value
	G_shiftxin1	Float	47	X axis motion IN – Input grip
	G_shiftxout2	Float	50	X axis motion OUT – Input grip
	G_shiftzup3	Float	15	Z axis motion UP (height) – Input grip

9_0_Tested_OK	G_num5	Int	2	Output place area - counts OK product program value
	G_shiftxin5	Float	50	X axis motion IN – Output OK place
	G_shiftzup5	Float	10	X axis motion OUT – Output OK place
	G_shiftxout5	Float	70	Z axis motion UP (height) – Output OK place
11_0_Tested NOK	G_num8	Int	0	Output place defective area – read NOK product value
	G_shiftxin8	Float	52	X axis motion IN – Output NOK place
	G_shiftzup8	Float	15	X axis motion OUT - Output NOK place
	G_shiftxout8	Float	50	Z axis motion UP (height) – Output NOK place
6_0_CAM_trigger	G_num10	Int	0	Camera trigger OK – OK product counter (decision module)
	G_num11	Int	0	Camera trigger NOK – NOK defective product counter (decision module)

4.3. MACHINE VISION PROGRAM STRUCTURE AND DETECTION

MV system triggering is executed using the cobot controller's control box, through digital outputs (DO). This evokes a program from Cognex In-Sight software. The product needs to be visually checked from two positions: 0 degrees and 180 degrees and is achieved using a smart fixture [6], the program follows the same structure. An example used for this study has 6 cables on one side and 6 cables on the other side with different colours. It is also possible that the same colour marker is used on the same side, but different functionality of the product.

A colour database was created in the MV system for each colour. This means that each cable went through colour training in different light conditions and constraint setups. Constraints setup includes a lower and upper boundary variation in the number of pixels being counted, see Fig. 4. As the quality of product functions is essential, correct product cable results must be all true. If any colour is not detected or is out of range, then the product will move to the defective area. While the MV triggering was executed through DO, the feedback for the cobot controller was sent through digital input (DI) channels. True value creates 1 and false value creates 0, which is used in the decision module. The decision module compares the values, and the controller directs to the corresponding sub-program for execution.

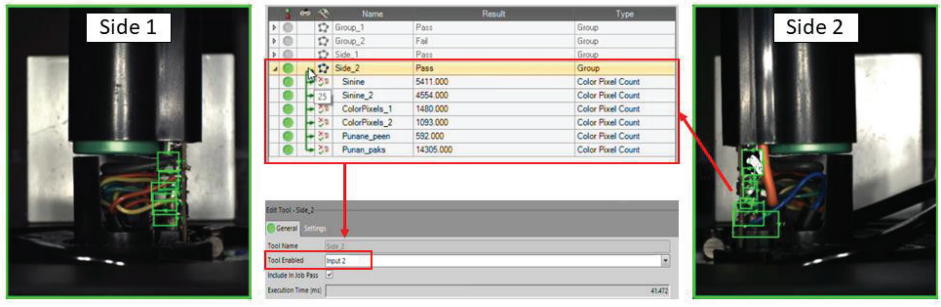


Fig. 4. An example of MV program structure

5. CBQC SETUP AND TESTING

This paragraph presents the overview of the CBQC setup and testing, introducing results. Our research is based on previous results of the authors' article [6], and lots of effort has been directed to programming and logic to meet the requirements of AI functions and increase the system's sustainability.

The proof of concept of the CBQC system has been achieved: Cobot can handle the products, adaptive gripper jaw design offers the required grip without damaging the product, MV detects necessary objects (cables) and colours, and the decision is made and cobot controller executes the information. We have run test cycles with the products with a speed of 40% which is 280 mm/s. The motion speed is the major parameter in this system cycle time and the time consumption for one product is 90 seconds. The motion speed can be increased (previously suggested 250-500 mm/s [6]), keeping sustainability in mind.

Our testing used random placement of different IoT modules from three models. We can state that zero defective or unsuitable models, from 350 products tested, did not pass the CBQC system. On the other hand, a new problem occurred during testing. Due to the changes in the lighting environment during daylight hours, approximately 8% of OK products were marked with NOK and sent to defective area. This problem must be solved with more consistent lighting conditions and decrease the influence of daylight.

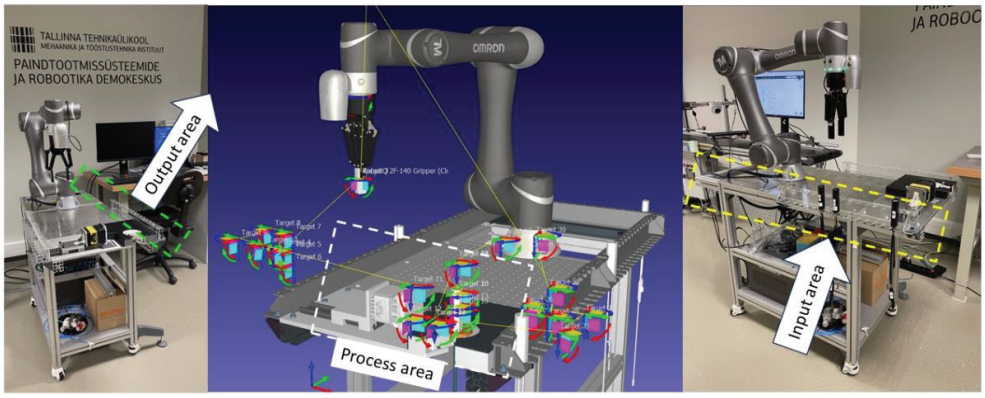


Fig. 5. Virtual and real cobot based quality control system [6]

6. CONCLUSION

In this study, the importance of AI functionalities in cobot-based quality control applications has been discussed. The integration and implementation of different equipment into a functional CBQC system is a complex assignment. Following structural rules and determining system and equipment limitations help to create boundaries for faster integration. AI functionalities such as Modbus protocol, and local and global variables enable to improvement of programming performance in terms of creating the multi-layer communi-

cation between system equipment in terms of hardware and software. This, on the other hand, improves the performance of the entire system.

In the practical use case, we have presented an approach how to classify the CBQC system program into modules, allowing a simplified overview and navigation for the user. This helps to solve any occurrences faster in the process or adapt new products into the CBQC in the 60% less of time consumption. Also, we presented the effective use of variables for making the system program five times more compact and easier to reconfigure. Either scaling up the program in terms of products or changing the system parameters. The time consumption for one product is 90 seconds with a speed of 40% of cobot. In terms of MV detection, it takes 2 seconds to detect both sides of the product together with smart fixture motion, where image recognition takes 200 ms per side. For future development, the possibility of machine learning functionality as part of AI functionality should be studied and discussed. During the future testing, we can collect more data (position of cables, changes in lighting environment, and common faults) and train machine vision system to adaptable detection system with real-time data. Renewable pattern database would keep any changes with the product more easily trackable.

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REFERENCES

[1] Eurofound, 2021, *Tackling Labour Shortages In EU Member States*, Publications Office of the European Union, Luxembourg.

[2] PIESKA S., KAARELA J., MÄKELÄ J., 2018, *Simulation and Programming Experiences of Collaborative Robots For Small-Scale Manufacturing*, 2nd International Symposium on Small-scale Intelligent Manufacturing Systems (SIMS), Cavan, Ireland, 1-4, https://doi.org/10.1109/SIMS.2018.8355303.

[3] BATTH R.S., NAYYAR A., NAGPAL A., 2018, *Internet of Robotic Things: Driving Intelligent Robotics of Future - Concept, Architecture, Applications and Technologies,* 4th International Conference on Computing Sciences (ICCS), Jalandhar, 151–160, https://doi.org/10.1109/ICCS.2018.00033.

[4] MOOR M., VAHER K., RIIVES J., KANGRU T., OTTO T., *Modern Robot Integrated Manufacturing Cell According to the Needs of Industry 4.0,* Proceedings of the Estonian Academy of Sciences, Tallinn, 202, 407–412, https://doi.org/10.1088/1757-899X/1140/1/012034.

[5] FRIEDMANN M., FLEISCHER J., 2022, *Automated Configuration of Modular Gripper Fingers,* Procedia CIRP, 106, 70–75, https://doi.org/10.1016/j.procir.2022.02.157.

[6] MOOR M., SARKANS M., RIIVES J., OTTO T., VAÑÓ J.M., *Methodology for Reconfigurable Cobot-Based Quality Control System for SME Production,* International Journal of Engineering and Technology, https://doi.org/10.7763/IJET (accepted, to be published).

[7] International Federation of Robotics, 2023.

[8] GAMBAO E., 2023, *Analysis Exploring Risks and Opportunities Linked to the Use of Collaborative Industrial Robots in Europe,* European Parliamentary Research Service.

[9] International Federation of Robotics, *2020, Demystifying Collaborative Industrial Robots,* International Federation of Robotics, Frankfurt.

[10] BIRGLEN L., SCHLICHT T., *2018, A Statistical Review of Industrial Robotic Grippers,* Robotics and Computer-Integrated Manufacturing, 49, 88–97, https://doi.org/10.1016/j.rcim.2017.05.007.
[11] ZHANG B., XIE Y., ZHOU J., WANG K., ZHANG Z., *2022, State-of-the-Art Robotic Grippers, Grasping and Control Strategies, as Well as Their Applications in Agricultural Robots: a Review,* Computers and Electronics in Agriculture, 177, https://doi.org/10.1016/j.compag.2020.105694.
[12] SIKDER A.K., PETRACCA G., AKSU H., ULUAGAC S., 2018, *A Survey on Sensor-based Threats to Internet-of-Things (IoT) Devices and Applications,* https://doi.org/10.48550/arXiv.1802.02041.
[13] TORCHIA M.S.M., *2019, IDC Forecasts Worldwide Spending on the Internet of Things to Reach $745 Billion in 2019,* IDC.
[14] RODRIGUES D., CARVALHO P., et al., 2022, *An IoT Platform for Production Monitoring in the Aerospace Manufacturing Industry,* Journal of Cleaner Production, 368, https://doi.org/10.1016/j.jclepro.2022.133264.
[15] PARSEC AUTOMATION CORP., 2023, *Parsec's 2023 State of Manufacturing Survey: Europe.*
[16] SINGH T., SINGH D., 2023*, Factories of the Future: Technological Advancements in the Manufacturing Industry*, Wiley.
[17] MATERNA Z., KAPINUS M., BERAN V., SMRŽ P., ZEMČÍK P., 2018*, Interactive Spatial Augmented Reality in Collaborative Robot Programming: User Experience Evaluation,* 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Nanjing, China, 80–87, https://doi.org/10.1109/ROMAN.2018.8525662.
[18] BIRGLEN L., 2019, *Design of a Partially-Coupled Self-Adaptive Robotic Finger Optimized for Collaborative Robots*, Auton. Robot., 43, 523–538, https://doi.org/10.1007/s10514-018-9802-x.
[19] EL ZAATARI S., MAREI M., LI W., USMAN Z., 2019, *Cobot Programming for Collaborative Industrial Tasks: an Overview*, Robot. Auton. Syst., 116, 162–180, https://doi.org/10.1016/j.robot.2019.03.003.
[20] ZHANG Y.-J., LIU L., HUANG N., RADWIN R., LI J., 2021, *From Manual Operation to Collaborative Robot Assembly: an Integrated Model of Productivity and Ergonomic Performance,* IEEE Robotics and Automation Letters, 6/2, 895–902, https://doi.org/10.1109/LRA.2021.3052427.
[21] NATIONAL INSTRUMENTS CORP, 2024, *What Is Modbus Protocol and How Does It Work?,* Retrieved March 12, https://www.ni.com/en/shop/seamlessly-connect-to-third-party-devices-and-supervisory-system/the-modbus-protocol-in-depth.html.
[22] PROMODEL CORP, 2012, *Building the Model: Advanced Elements – Variables – Local Variables,* https://www.promodel.com/onlinehelp/ProModel/86/Content/Topics/C-06%20-%20Local%20Variables.htm.
[23] CARNEGIE MELLON ROBOTICS ACADEMY, 2024, *Global Variables*, https://www.robotc.net/teaching_rc_cortex_v2/lesson/media_files/hp_global_variables.pdf.

Appendix 4

Publication IV

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KNOWLEDGE-DRIVEN BASED PERFORMANCE ANALYSIS OF ROBOTIC MANUFACTURING CELL FOR DESIGN IMPROVEMENT

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ABSTRACT

Manufacturing companies must ensure high productivity and low production cost in rapidly changing market conditions. At the same time products and services are evolving permanently. In order to cope with those circumstances, manufacturers should apply the principles of smart manufacturing together with continuous processes improvement. Smart manufacturing is a concept where production is no longer highly labor-intensive and based only on flexible manufacturing systems, but production as a whole process should be monitored and controlled with sophisticated information technology, integrated on all stages of the product life cycle. Process improvements in Smart Manufacturing are heavily reliance on decisions, which can be achieved by using modeling and simulation of systems with different analyzing tools based on Big Data processing and Artificial Intelligence (AI) technologies.

This study was performed to automate an estimation process and improve the accuracy for production cell's performance evaluation. Although there have been researches performed in the same field, the substantial estimation process outcome and accuracy still need to be elaborated further.

In this article a robot integrated production cell simulation framework is developed. A developed system is used to simulate production cell parametric models in the real-life situations. A set of rules and constraints are created and inserted into the simulation model. Data for the constraints were acquired by investigating industries' best production cells performance parameters. Information was gathered in four main fields: company profile and strategy, cell layout and equipment, manufactured products process data and shortcomings of goal achievements or improvement necessary to perform. From those parametric case model, a 3D virtual manufacturing simulation model is built and simulated for achieving accurate results.

The integration of manufacturing data into decision making process through advanced prescriptive analytics models is a one of the future tasks of this study. The integration makes it possible to use "best practice" data and obtained Key Performance Indicators (KPIs) results to find the optimal solutions in real manufacturing conditions. The objective is to find the best solution of robot integrated cell for a certain industry using AI enabled simulation model. It also helps to improve situation assessment and deliberated decision-making mechanism.

Keywords: Knowledge driven manufacturing, robot-cell performance analysis, data analytics, simulation applications, digital twins.

1. INTRODUCTION

In 2011 the Industry 4.0 philosophy was widely introduced, followed by a systematic and determined development in this field. An architecture based on seven pillars has developed related to Industry 4.0 (I4.0), which describes the modern production system more narrowly and the main development trends of all production more broadly. As production in European countries accounts for a large share of GDP at 24.9% [1], development of this sector has a major impact on all other sectors. Nevertheless, major changes are taking place in the population structure due to low birth rates and high life expectancy. The last decade has seen an increase in the proportion of people aged 65 and over in the European Union of more than 2.6%, leading to an increase in the dependency ratio to over 21% [2] of the total population. There are currently just over three people of working age for every person aged 65 or

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over [2]. This indirectly affects the number of employees in the industrial sector and there is rather pressure to increase the growth of value added in production, then in future the low birth rate directly affects the share of people of working age in the industrial sector.

In addition to labor market problems, European industry is under constant pressure from cheaper production in developing countries. Over the years, exports to the European Union have been in constant profit, growing by 16.2% in 2016-2018 [3].

The EU is one of the world's leading environmental regulations. Environmental regulations generally require polluting facilities to undertake abatement activities and may impose costs on businesses. Thus, regulatory differences across firms, sectors or jurisdictions can cause changes in relative production costs. Differences in environmental regulations can thus alter the competition between firms by changing their relative production costs. [4]. These difficulties drive the development of industrial technologies for reducing the labor force, using resources efficiently, and shorting the developing time of the product.

The trends of digitalization have a great importance in US manufacturing [5]. More firms are making footprint decisions using a "total factor performance" approach that considers logistics, lead time, productivity, and risk as well as proximity to suppliers, other company operations, and final demand. Fundamentally, manufacturers need to identify strategic use cases that are linked to their digital initiatives and business strategy. Furthermore, they need to consider how to begin working alongside machines in a more automated and data driven way.

Large companies with more resources are more likely to be able to invest in and develop new I4.0 technologies to stay competitive and tackle these challenges. However, small and medium-sized enterprises (SMEs) are certainly not able to adapt similar solutions. This is also one of the reasons why technical solutions for companies of different sizes in the industrial sector should be considered according to the company's investment potential. It is important to ensure the competitiveness of small and medium-sized enterprises by finding solutions to labor problems, trying to increase productivity with equivalent resources, shorten the time to market, and produce products in compliance with current environmental standards. The biggest challenge for SMEs is to fulfill these conditions simultaneously. It certainly cannot be a single solution, but rather a continuous process improvement that could be based on the well-known Deming's Plan (P) - Do (D) - Check (C) - Act (A) cycle, one possible implementation of such kind of work has been discussed in high performance workplace design model [6].

Currently, SMEs use different types of production units such as single station automated cell, automated assembly system, flexible manufacturing system, computer integrated manufacturing systems, reconfigurable manufacturing systems and in these units the level of automation and intelligence vary greatly. Analyzing the current situation in the industry like digitalization via digital twin, communication, standardization, flexibility, customization, real-time monitoring, predictive maintenance, and industry lower level evaluations, upper level self-optimization and self-configuration [7, 8] and comparing it I4.0 principles lead to separate development areas for each company that should be addressed. This paper described a digital analyzing tool based on continuous process improvement philosophy to optimize production cell workflow for the SME´s. Some of the key aspects for optimization are workforce shortage and age peculiarity, assessment of investment compared to production output and maintaining a competitive advantage in high environmental regulations region.

2. MODERN MANUFACTURING

Modern manufacturing systems have evolved into complex ecosystems. Digital manufacturing and smart factories are becoming the norm in manufacturing, they depend on leverage of connected devices and technologies, numerically controlled machines and robots, advanced analysis with artificial intelligence, IoT, digital twins, advanced planning and control capabilities, which operates through the entire value chain. In addition, these devices must be capable of sensing their environments and interacting with one another. Simulation through digital twin is the technology for decreasing the time to design manufacturing systems and having information for decision making in performance analysis. Development tools related to I4.0 such as advanced simulation have great importance in industrial applications. Hence, there is a need and demand of digital solutions from production SME, which would help effectively use implemented technology and involved recourses. However, the studies offered and developed specialized digital solutions for production SMEs are lacking and need to be addressed comprehensively.

2.1 Manufacturing System Knowledge Based Architecture

Knowledge-based engineering (KBE) is the application of knowledge-based systems technology into the domain of manufacturing design and production. Production systems (robot-cell) can be defined as a kind of cognitive architecture, in which knowledge is represented in different forms. So, typically robot-cell based workplace as a part of a production system is a complex system with a specific architectural structure. To have a better understanding, according to Scholz-Reiter, a physical hierarchical levelling system should have three levels with various parameters: [9]

1. The system level, a production can be defined as stations or cells which are usually linked with predicted storage and transport systems;
2. The sub-system level, a workplace is considered as a pack of support resources for operations (e.g. robots and different devices);
3. The machine level, an environment with different tools, grippers, data, programs according to the necessity of the required equipment.

Previously stated physical hierarchical levelling system is combined with components (e.g. CNC machine or a

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manipulator). According to the complexity of different level systems, these resources can be described in several levels. In this study, we have been using two different robot cells which range between Sub-system to System level in principle. It allows to define certain constraints and input for work cells used for case studies.

2.2 Manufacturing System Design Inputs

Manufacturing System Design (MSD) inputs are based on numerous different parameters or keywords for "how to design". The wide range of variables makes it complicated to select important design input parameters (e.g. enterprise needs and objectives, external factors, controllable factors, constraints and targets), but precisely described manufacturing vision that leads to refined result in design process. Moreover, not all these factors affect the MSD directly, factors such as Market Uncertainty (MU), Product Volume (PV), Product Mix (PM), Frequency of Changes, Complexity, Process Capability, Worker Skill, Type of organization, Time to first part, Investment, Available/Existing Resources pointed out major parameters [10]. Starting with MU, it can be defined with fluctuations of a product demand. The demand affects manufacturing operation, creating an over or under capacity in the manufacturing system. Another important factor which is tightly connected with MU is the Product volume. Maximizing the PV determines manufacturing physical design by affecting factors like needed space, machine selection and layout. Furthermore, MSD process certainly includes the level of flexibility which can be associated with Product Mix. If the manufacturing system is expected a large product mix, it would lower the product volume produced per part. On the other hand, not all these factors stated above favor the MSD process. For example, the amount of investments is treated as a constraint and limits available choices to the designers. This can be based on several variables such as cost of implementation, payback period or time needed for MSD. For investments, we can consider Existing Resources to be a constraint in the design process. These availabilities such as time, finances, existing technologies can set limitation to the complexity which are expected from designed manufacturing system. All in all, these crucial factors should be considered carefully to use as inputs for fundamentals of manufacturing system design which should be chosen according to specific needs of enterprise.

2.3 Advanced Analytics

Advanced Analytics (AA) are becoming more and more vital for making so called "best decisions" on today's field of manufacturing. AA enables companies to efficiently and effectively make both narrow and extensive data-and modelling decision and facilitates on how to capitalize within the short-, medium- and long-term activities. Support for the decision maker comes to an automated process with visualized output rather than manual calculations on spreadsheet. AA can be divided into three computerized data processing analytic methods which are listed below:

- *Descriptive analytics:* accounting and analysis of historical data. Used in back casting practices and forecasting of seasonal demands.
- *Predictive analytics:* considers near past data to predict coming future trends, biases, tendencies, behaviors, etc., through causation and correlation.
- *Prescriptive analytics:* finds or prescribes the best mode, route, manner or moves to operate (outputs) based on given data and models (inputs). [11]

Data Analytics application requires a sufficient available database. By combining existing information gathered from MES and ERP databases with the effects of external factors, it is possible to use advanced analytics to extend the simulation model so that the forecast for the future is as real as possible. Possible application scenarios could be from manufacturing parameters optimization, predictive maintenance, available capacity or capacity needs prognosis and process performance among others [12]. The analysis process itself is designed cyclical nature and consists mainly of following steps [13]:

- Business understanding - objectives and requirements from a business perspective,
- Data understanding - data collection, data quality,
- Data preparation – construction of final dataset,
- Modeling – applying different modeling techniques. Some of the main methods used for modeling is this research are correlation, regression and prognosis,
- Evaluation – verifying model and dataset,
- Deployment – presenting results in a form that can be used.

2.4 Performance Monitoring

Key Performance Indicators (KPI) should be consider as a company vital sign, describing the actual situation and goal fulfillment. Using those as a tool, provides an opportunity to measure, analyze and make decisions for keeping production on track. At the same time, it is possible to identify bottlenecks in production, possibility to increase the effectiveness of employees and machine or to monitor the progress of production orders. Today, KPI monitoring is a multi-level, real-time process which begins at the shop-floor and reaches to the company strategic level, concentrating collected information for higher level KPIs. Selection of KPI for different companies and for different levels is generally a multi-criterion decision-making problem (MCDM) and it is important that the choice reflects the subject as accurately as possible. KPI selection problem have been addressed in those following researches [14, 15].
Solution for SME have been developed to assess the production unit performance [16], focused particularly on the evaluation process: Define System, Selection of KPIs, Process Modeling Simulation, Data Collection and Analysis and finally, Real Time Visualization. Hierarchical linking between KPIs through all levels have been mapped. The proposed KPIs are shown in Table 1. for SME production unit and are used in simulation model. Starting from the third and lowest level where inputs are measured directly from workplace or machine and ending at the highest where outputs are calculated.

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TABLE 1. SELECTED KPI HIERARCHY

Level	Performance Indicators
I Strategic	Utilization
	Overall Equipment Effectiveness
	Throughput
	Discounted Payback Period
II Tactical	Availability
	Performance
	Quality
	Planned Production Time
	Actual Production Rate
	Set-up Time vs. Cycle Time
	Operating Time/Idle Time vs. Cycle Time
III Shop-Floor	Total Products Produced
	Finished Products
	Rejected Products
	Activity Processing Time
	Operating Time
	Ideal Processing Time
	Total Run Time

2.5 Production Cell Efficiency Analysis

Over the years many decision support systems (DSS) has been developed to help decision makers to select most functional and cost-effective equipment for production cell. One of the IR manufacturing cell design and redesign DSS system are shown in Fig 1.

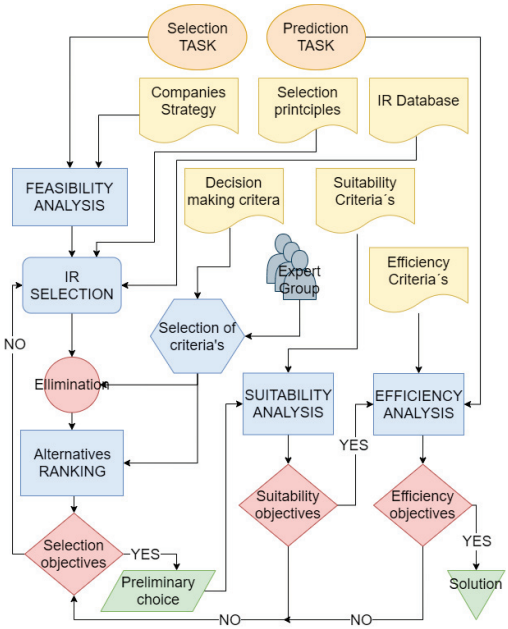


FIGURE 1: IR SELECTION DSS GENERAL MODEL [19]

Primary task is to check the cell architecture and technical parameters best suited for a selected job, and the reverse or prediction task consists of the analysis of optimal utilization of the implemented robot-cell in a company. One of the key components of reverse task is production cell efficiency analysis. The efficiency analysis evaluates the designed or installed solution, based on best competences. For adequate estimation of production unit manufacturing efficiency and assessment of production unit process failures, the whole system, components and their relations must be evaluated [17, 18]. Next section focuses on the development of the efficiency analysis module.

3. METHODOLOGY

To develop the efficiency analysis module of the production unit, a case study methodology was applied, for which the necessary theoretical material was investigated in the literature review. The proposed model (Fig. 2) is intended for computerized performance assessment of a production unit based on the objectives set in the company's strategy and industry-based collected production data. The model can be used to evaluate a company production process (CNC production cell) for a comparison with an ideal process set up in the proposed model. In addition, the proposed model is a useful tool in the design phase of a new production unit, as it allows to assess productivity based on the collected production information. The advanced data analysis of the model provides information for further improvements.

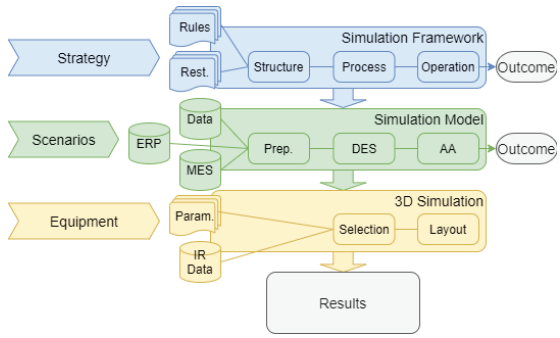


FIGURE 2: PRODUCTION SYSTEM EFFICIENCY ANALYSIS

The efficiency analysis is divided into three steps as shown in Fig. 2., where each step increases the accuracy of the selection. In the first step, production type, production volume and production technology are determined for the designed or redesigned cell. Inputs for this step are the design rules and constraints [10]. At the end of this step, the general requirements of the production unit have been determined. In second step, a simulation model is created according to the selected rules and constraints. Different scenarios are inserted into the developed model and the optimal scenario or scenarios are selected. At the end of this stage, a parametric model of the cell has been developed with a simulated technical economic result. At last step 3D simulation model is create based on the information

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provided earlier and most accurate results in different layouts and settings are acquired.

Information and data for the simulation model have been collected through various studies and databases. Studies on companies' products, production capacity and production units have been included [20, 21]. Production-specific data have been collected from companies' Manufacturing Execution Systems (MES) databases. The parameters and sub-parameters are selected according to the literature [10] and vary depending on the production capacity and type of the company. A list of the parameters used are given in table 2. From companies MES databases, the list and order of operations, their planned and actual cycle times, amount of scrap and rework needed to manufacture the products are used. The number of operations, cycle times and the number of reworks give an estimation of the product complexity.

TABLE 2: PARAMETER AND SUB-PARAMETER LIST

Parameter	Sub-parameter
Company	No of production machines
	Shifts
	Investment
Manufacturing	Operation orders
	Volume
	Performance
Operation	Start Time
	End Time
	Availability
	Performance
	Quality
	Process Capability
Product	Complexity
	Variety
	Quantity
	"New Products"

Part of the collected data (No of production machines, Shifts, Investment), the smallest in volume, can be used in the raw form. The second part of the data (product variability, quantities, new products) was processed statistically and their distribution was calculated. The third part and largest of the data were processed using artificial neural network classification [22, 23]. Neural Designer software was used for this purpose.

3.1 Manufacturing Cell Model

The manufacturing cell model is based on robot-based manufacturing cell Performance Evaluation Model (PEM) [19] and is programmed using Discrete Event Simulation (DES) software, Rockwell Automation Technologies Inc. Arena. An overview of the model is given in Fig. 3 and one of the sub-models in Fig 4.

The model is used to simulate different production orders simultaneously, like in "real life", according to their operation sequence and order specific data. Order can exit the system only when all the necessary operation and occasional rework have been performed, and order has been successfully completed. Simulating concurrently, it is possible to assess the combined effects of orders, identify bottlenecks and incorporate improvements, which are directly reflected on production unit performance records.

Entities for the model were defined as an order where part production information (operations, cycle times, quality parameters, etc.) together with production volume are assigned. Outputs were defined as completed orders and rejected orders. Throughput and net value are calculated for each completed order. Similarly, unearned value is calculated for rejected orders. After simulating parts and volume by their distribution a KPI can be calculated. For this model a simple KPI selection of total production unite Utilization, Net Income and Discounted Payback Period were included. At first the model asses the existence of production capacity, in case the operations are busy and there is no free capacity, the order is sent to Rejected orders.

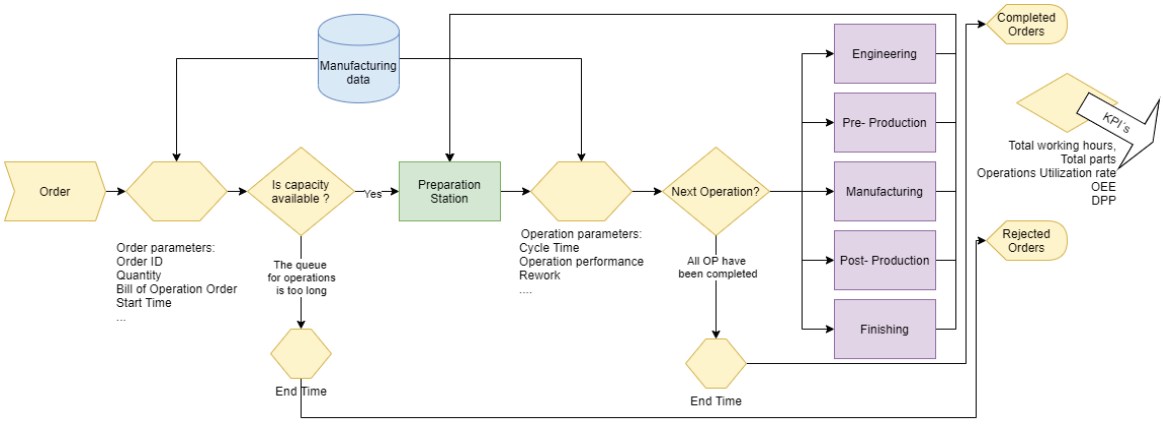


FIGURE 3: MANUFACTURING CELL MODEL

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If the production unit has free capacity to utilize, the order will start to execute according to the order bill of operation BOO list.

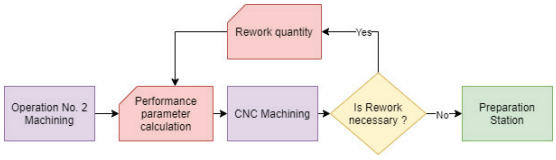


FIGURE 4: MANUFACTURING CELL SUB MODEL

In the model, the operations are described more broadly than normally in industry production planning. The model combines similar industrial operations such as turning, milling, bending into one manufacturing operation with a cycle time and operation specific productivity, availability and quality. Fig. 2. The following operations are used in the model: Engineering, Pre-processing, Manufacturing, Post-processing and Finishing. Each operation in the model is associated with a database, from which the required data for the operation is loaded according to the product and the operation cycle time and calculated according to equation (1).

$$O_{Th} = \frac{Q * CT * \sqrt{P_O * P_P}}{C * A} \quad (1)$$

Where O_{Th} - represents operation throughput time, Q - production quantity, CT - planned cycle time, P_O - operation performance value, P_P - part performance value, C - capacity and A - availability. Similarly, rework RO equation (2). is calculated where a product-specific quality coefficient P_q directs Q_P products to reprocessing. Normative times to move batches are set between operations. When all operations for the batch have been performed, the batch is sent to Completed Orders.

$$R_O = Q * P_q * Q_P \quad (2)$$

4. CASE STUDY

The validation of the model was accomplished by using cases studies. Two cases were chosen, a CNC manufacturing cell and a robot welding cell. The reason to select those cases was that there are large number of such production cells available in the regional industry. Another consideration was the availability of necessary production data and the structure of collected data. During the validation process, the correlation of production unit performance values and KPI´s, was observed at the same production program.

4.1 CNC Manufacturing Case Study

For the CNC Manufacturing case a small company was chosen. The company is manufacturing small and medium sized mechanical components for industrial machines and medical devices. Work is organized mainly in one shift and sometimes in two shifts. This study focused on the CNC machine-tending cell shown in Fig. 5. The production cell consists of medium sized turning center, co-working robot connected to it and WIP (work in progress) storage. The KPI where chosen as following: Throughput, Total Number of Orders, Total Products Produced, Overall Equipment Effectiveness, Utilization TPU and Discounted Payback Period.

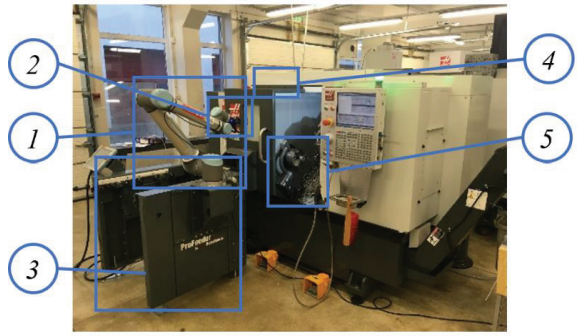


FIGURE 5: CNC MACHINE-TENDING CELL

Where: 1 - Co-working robot, 2 - universal prism gripper, 3 - work in progress storage, 4 - part overturn position, 5- machining position. Operations for the cells normal workflow are listed and explained in table 3. Average operations availability and performance was acquired from the company MES database. Order volume distribution, parts distribution and part cycle times for the operation where acquired from the company ERP system and MES database.

TABLE 3: CNC MANUFACTURING CASE STUDY OPERATIONS

Op.	Operation	Explanation
1	Engineering	The order has been accepted and planned for production starts.
2	Engineering	CAM programming the part
3	Pre- Production	CNC machine and IR robot setup and test run.
4	Manufacturing	Blanks are inserted to the WIP and manufacturing is started.
5	Post- production	Quality control are carried out
6	Finishing	The batch is finished, and the setup is taken down

For further configuration a 3D simulation is used, see Fig. 6. Visual Components 4.2 software was used to perform the analysis. By experimenting with different layout variations, it is possible to find the most optimal solution for the company production floor. As in this case the real environment already exists, the simulation was used only to optimize the IR robot position according to robot reach. For the new layout design, different configuration robot can be used at different mount locations and these changes can be tested in the 3D simulation environment.

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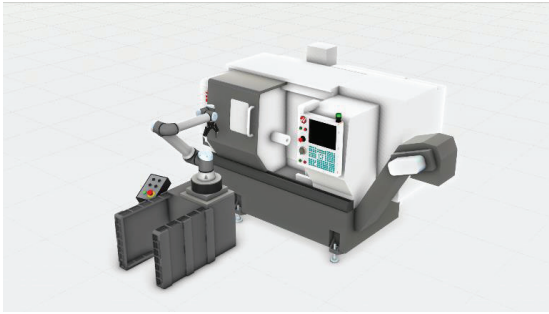


FIGURE 6: CNC MANUFACTURING CASE STUDY SIMULATION MODEL

4.2 Robot Welding Case Study

For the second case study a robotic welding unit of a small manufacturing company has been selected similarly as before. The company manufactures boiler housings and small assemblies for forest machines in small-scale serial production conditions. Six different products have been setup in this production unit. The work is organized in one shift. The production unit operator assembles parts from a pre-welded assembly in the jig, which is placed into the production unit for final welding. The KPI where chosen similarly as previous case.

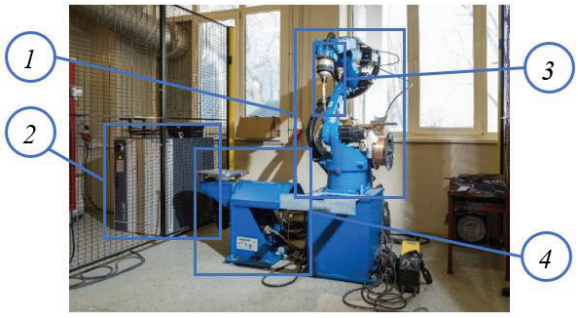


FIGURE 7: ROBOTIC WELDING PRODUCTION UNIT

The production unit is shown in Fig. 7. where: 1 - robot manipulator, 2 - controller 3 - welding unit, 4 - programmable L-type positioners.

Operations for the regular workflow are listed and explained in table 4. For the welding cell case study 3D simulation, shown in Fig. 8, MotoSim EG-VRC software was used. As with the previous case 3D analysis, the optimal robot position was determined, same here but the main concern was whether the robot can reach all the assembly welding seams on the L positioner. Since the welding parameters had already been validated, it was possible to obtain accurate welding cycle times from the simulation.

TABLE 4: ROBOTIC WELDING CASE STUDY OPERATIONS

Op.	Operation	Explanation
1	Engineering	The order has been accepted and planned for production starts.
2	Engineering	CAM programming or teach in the assembly
3	Pre- Production	IR robot setup and test run.
4	Pre- Production	Spot welding parts in assembly jig
5	Manufacturing	Assembly are inserted to welding table and manufacturing are started.
6	Post- production	Quality control are carried out
7	Finishing	The batch is finished, and the setup is taken down

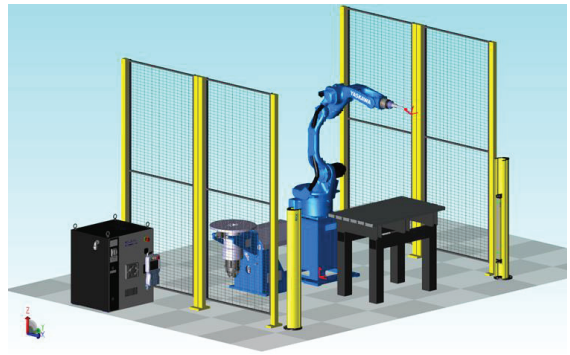


FIGURE 8: ROBOTIC WELDING CASE STUDY SIMULATION MODEL

4.3 Results and discussion

The production unit model was simulated using 10 preset products with different configuration, the minimum parts quantity was 10 and the maximum 500 parts per order. The simulation duration was 4.5 years, which in total was 9,000 working hours, working in one shift. As a result, a total of 100 thous. parts were produced during 430 orders, making the average number of parts per order 230 pc. The overall utilization rate for the production unit was 40% during this period, with CNC machining being the highest, with a utilization of 83% in some cases. CNC machining center overall equipment effectiveness OEE lowest 52%, highest 90% and average value 87%. Based on these data, the calculated discounted payback period DPP was 3.2 years.

The second case study production model was simulated for continuous work of 4000 hours, 2 years. As a result, 1400 assemblies where welded during 120 orders. The overall utilization rate for the production unit was 53% during this period, with robot welding operation being the highest, utilization of 80% in some cases. Overall equipment effectiveness OEE average value was calculated 72%. Based on these data, the calculated discounted payback period DPP was

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4.8 years. Comparing the KPI numerical values obtained in both simulations with the actual KPI values of the company's production unit, the variation remains within 25% of the boundaries.

5. CONCLUSION

In this research, various possibilities were explored how to model semi robotized production unit workflow, using existing production information as input data. As a result, a methodology was developed to assess the performance of a production unit interactively by comparing it in digital twin modeled ideal process, where one of the main elements was a production unit knowledge-driven based discrete simulation operation model. The developed model was validated by using two case studies and modeled results compared and verified to the companies actual KPI´s. As a last step, a 3D simulation was created, based on the previous results, which was used to refine or reconfigure the production unit. Based on the developed methodology, it is possible to analyze the performance of an existing production units. It also helps to validate a new design of a production cell/unit and optimize their outputs through prescriptive analysis.

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REFERENCES

[1] “Structure of the euro area economy”, accessed May 08, 2020, https://www.ecb.europa.eu/mopo/eaec/html/index.en.html.

[2] “Population structure and ageing”, accessed April 15, 2020, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_structure_and_ageing/et#Rahvastiku_vananemise_varasemad_ja_tulevased_suundumused_Elis.

[3] European Commission, 2020, “Report on the Generalised Scheme of Preferences covering the period 2018-2019”, JOIN (2020) 3 final.

[4] Dechezleprêtre, A., Sato, M., 2018, Green policies and firms’ competitiveness, OECD, Paris.

[5] McKinsey Global Institute, 2017 “Making it in America: Revitalizing US manufacturing”.

[6] Lõun, K., et al. 2013, “High-performance workplace design model”, Estonian Journal of Engineering, Vol.19, No. 1, pp. 47 – 61.

[7] Qin, J., Liu, Y., Grosvenor, R. 2016 “A Categorical Framework of Manufacturing for Industry 4.0 and Beyond”, Procedia CIRP 52, pp.173 – 178.

[8] Kuts, V., Modoni, G. E., Otto, T., Sacco, M., Tähamaa, T., Bondarenko, Y., Wang, R. 2019. “Synchronizing physical factory and its Digital Twin through an IIoT middleware: a case study.” Proceedings of the Estonian Academy of Sciences, Vol. 68 (4), 364−370.

[9] Benkamouna, N., ElMaraghyb, W., Huyeta, A., L., Kouissa, K., 2014 “Architecture Framework for Manufacturing System Design”, Procedia CIRP 17, pp. 88 – 93.

[10] Vaughn, A., Fernandes, P., Shields, J., T., 2002, “Manufacturing System Design Framework Manual”, Massachusetts Institute of Technology, Cambridge.

[11] Menezes, C., B., Kelly, J., D., Adriano, G., L., Le Roux, C., G. 2019, “Predictive, Prescriptive and Detective Analytics for Smart Manufacturing in the Information Age”. IFAC PapersOnLine 52-1, pp. 568–573.

[12] Groggert, S., Elser, H., Ngo, H., Q., Schmitt, R., H., 2017, “Scenario-based Manufacturing Data Analytics with the Example of Order Tracing through BLE-Beacons” Procedia Manufacturing 24, pp. 243–249.

[13] Chapman. P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., Wirth, R., 2020, “C RISP-DM 1.0 Step-by-step data mining guide”, SPSS Inc.

[14] Kibira, D., Feng, S., Brundage, M., Morric, KC., Leong, S. 2017, “Procedure for selecting key performance indicators for sustainable manufacturing”. Proceedings of the ASME 2017 International Manufacturing Science and Engineering Conference. MSEC2017.

[15] Kaganski, S., Majak, J., Karjust, K., and Toompalu, S. 2017, “Implementation of key performance indicators selection model as part of the Enterprise Analysis Model.”Procedia CIRP, Vol.63, No. 1 pp. 283-288.

[16] Mahmood, K., Lanz, M., Toivonen, V., Otto, T. 2018, “A Performance Evaluation Concept for Production Systems in an SME Network”, Procedia CIRP 72, pp. 603 – 608.

[17] Kangru, T., Riives, J., Otto, T., Kuts, V., Moor, M., 2020, “Optimization of decision-making process in industrial robot selection” Journal of Machine Engineering, Vol. 20, No. 1, pp.70 – 81.

[18] Mahmood, K., Shevtshenko, E. 2015, “Analysis of machine production processes by risk assessment approach.” Journal of Machine Engineering, Vol. 15 (1), 112−124

[19] Kangru T., Riives J., Otto T., Pohlak M., Mahmood K., 2018, “Intelligent Decision-Making Approach for Performance Evaluation of a Robot Based Manufacturing Cell.” Proceedings of ASME Mechanical Engineering Congress and Exposition, 2, ASME, USA, 1–10.

[20] Kangru, T., Riives, J., Mahmood, K., Otto, T., 2019, “Suitability analysis of using industrial robots in manufacturing”, Proceedings of the Estonian Academy of Sciences, Vol. 68, No. 4, pp. 383 – 388.

[21] Vaher, K., Kangru, T., Otto, T., Riives, J., 2019, “The Mobility of Robotised Work Cells in Manufacturing”, Proceedings of the 30th DAAAM International Symposium, pp. 1049-1055.

[22] Hassani, E., Mazgualdi, E., Masrour, T., 2019, “Artificial Intelligence and Machine Learning to Predict and Improve Efficiency in Manufacturing Industry”.

[23] Saric, T., Simunovic, G., Svalina, K., 2016, “Estimation of machine time for cnc manufacturing using neural computing”, Int j simul model Vol. 15, No. 4, pp. 663 – 675.

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Appendix 5

Publication V
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learning factory, digital factory,
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RECONSTRUCTING A MANUFACTURING LABORATORY TO A LEARNING FACTORY: A TTK UAS CASE STUDY

The rapidly developing manufacturing industry constantly needs top specialists to ensure sustainability (resource optimisation, production efficiency, sustainable products) and to implement the latest know-how (digitalisation, big data analytics, artificial intelligence). Those requirements, in turn, place higher demands on universities, curricula, teaching staff and, above all, laboratories to teach the concept of a smart factory. TTK University of Applied Sciences (TTK UAS) has come to an understanding that renovation of existing production laboratories is unavoidable. Keeping this in mind, a study needs to be conducted to investigate best practices and strategies to develop a new concept that best suits TTK UAS. In this article, the authors examine how to renovate and update the existing university laboratories (production, measurement, CAD/CAM) using simulation software with a Learning Factory concept in mind while still ensuring research development capability. Using the case-study methodology, factory automation simulation software, and a new pedagogical approach, the TTK UAS industrial engineering laboratories are functioning as a cluster, achieving higher learning and R&D efficiency.

1. INTRODUCTION

Labour market trends have recently changed significantly. One of the main reasons is the COVID-19 crisis and the broader adoption of various AI technologies. Previous trends, such as robotization and automation, can also not be ignored.

The WEF study of future jobs in the industry shows a decrease in simple manual labour jobs, especially in assembly, and an equivalent increase in process-based jobs, such as welding, mold-making, etc. [1]. A general conclusion can be drawn that the industry is reorganizing, replacing lower and simpler skillset jobs with automated processes, and creating more jobs requiring specialized skills and knowledge. Such a tendency is also confirmed by a different study [2], which for the near future predicts a 27% decrease in physical and manual labour, a 17% decrease in the need for basic literacy and numeracy skills, a 58% increase in special technological skills, a 33% increase in social skills (taking the initiative and

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leadership) and 24% increase in higher cognitive skills compared to the 2016 skillset. The decrease in physical and manual labour can be explained by more comprehensive automation in the industry and the growth of technological skills needed by linking different technologies (machine learning and automation). Analytical thinking, creative thinking, and technological literacy have become essential skills in 2023 in the view of employers [1].

Very rapid changes in organisational culture were triggered by the COVID-19 crisis. It is possible to divide organisational development models into pre-crisis and post-crisis models. The post-crisis changes in the institution's work organization were nothing new. The main developments were related to agile and flexible work, i.e. Smart Working (SW). Previously, such models were mainly applicable to white-collar workers and some service economy sectors. After the crisis, the manufacturing industry had to adapt and rethink its work organisation to prevent production stoppages and ensure sustainability. Still, it is important to understand that the SW concept, based largely on remote work, doesn't completely apply in manufacturing. Production processes can only be carried out with the assistance of equipment, and therefore, it is usually impossible to separate the person from the process. Various sociotechnical models have emerged, summarised as Industrial Smart Working (ISW) [3, 4]. ISW focuses on greater integration of humans, organisation and technology, which does not remove humans from the production process but facilitates and supports the interaction between humans and machines.

Due to previous, entrepreneurs must constantly strive to acquire qualified labour in a rapidly changing environment. Undoubtedly, universities and higher education institutions also must go along with these changes and, in some cases, anticipate them to ensure that students are given the fundamental knowledge and skills to develop top specialists in the industry.

2. LEARNING FACTORY

Learning Factory (*LF*) is a partly artificial environment that combines academic teaching, learning, scientific research and industrial production capacity into one test platform for simulating interdisciplinary scenarios [5–7]. Students of various curricula, lecturers, and industrial specialists are involved in the scenarios. In the design and development of the laboratory base, it is essential to follow the sectoral development trends. The European Factories of the Future Research Association (*EFFRA*) has proposed the following key development areas [8]:

- Advanced manufacturing processes;
- Adaptive and smart manufacturing systems;
- Digital, virtual and resource-efficient factories;
- Collaborative and mobile enterprises;
- Human-centred manufacturing;
- Customer-focused manufacturing.

The purpose of creating an LF has to be similar to industry – developing and producing a product or service, starting from the development and ending with disposal while simulating

or performing all the processes in between. This approach has shown better results compared to classical learning for the acquisition of knowledge and skills [9].

2.1. TTK UAS LEARNING FACTORY

At TTK University of Applied Sciences (TTK UAS), like in many other universities, various technology laboratories have been created to study industrial engineering. The study process is carried out by focusing only on one technological process at a time and performing the practical work necessary to connect theoretical knowledge. Laboratories work separately, and the connections between them can often go unnoticed by students. Based on the advantages of the LF concept, changes must be introduced to the existing laboratory base of accordance with the needs of Industry 4.0 (I4.0) [10].

Figure 1 shows the simplified process after reconfiguration. It begins with the customer (placing an order) and ends with the customer (receiving the order from the warehouse and preparing an invoice).

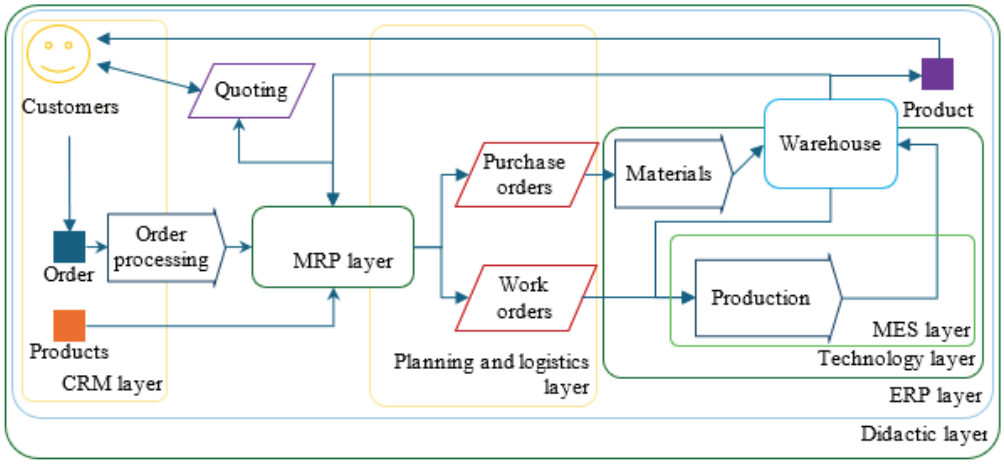


Fig. 1. Conceptual model of TTK UAS LF work process

The process is covered by different layers that ensure the necessary competencies. The layers and their competencies are listed below:

- Technology – All physical equipment (CNC turning and milling centres, machine tending and transport robots, Tools) and software (CAD/CAM/CAE). The selection of equipment is based on the suitability analysis [11];
- Material Requirement Planning – product, service information (BOM, BOO, deadlines) is analysed, planned and evaluated;
- Customer Relationship Management – collection, processing and planning of activities for customers and people valuable to the company;

- Planning and Logistics – internal and external logistics management;
- Enterprise Resource Planning – planning and management of the factory as a whole;
- Didactic layer – covers all previous layers, responsible for using optimal teaching methods and techniques.

3. PEDAGOGICAL APPROACH

To carry out the teaching process effectively, it is not enough to change only the learning environment. To get the best results, we must introduce changes to the teaching methodology and the teaching process. Based on the literature review, the teaching methodology that ensures effective assimilation of engineering education comprises the psycho-didactical model of engineering Fig. 2 and the competency model of engineering educators Fig. 3.

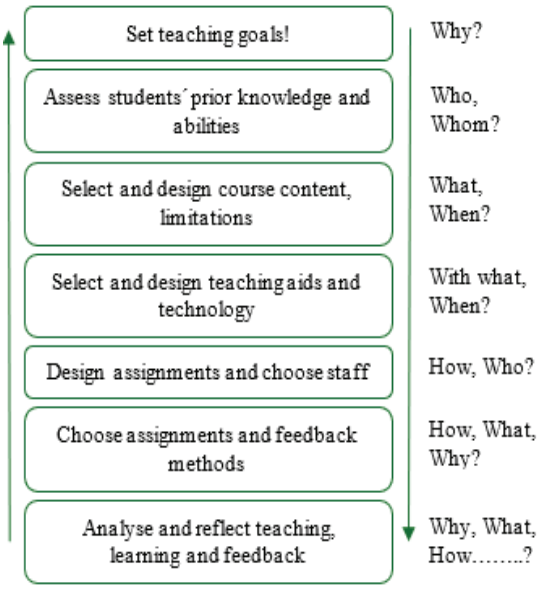


Fig. 2. Psycho-Didactical Model of Engineering Pedagogy [12]

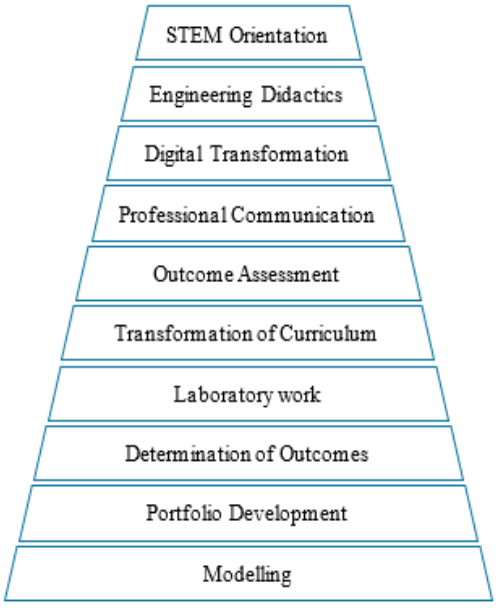


Fig. **3.** Competency model of Engineering Educators [13]

The teaching process must be a well-thought-out whole, divided into lecture-based sprints and independent and extra work. Since LF teaching is integrated between different fields, it is extremely important that the cooperation between the lecturers and specialists is sufficient, and information moves quickly for corrections in the lecture plans.

Conducting effective and inclusive lectures and sprints requires various methods and skills Fig. 3. The common denominator of the methods is STEM, which stands for Science, Technology, Engineering, and Math.

4. CASE STUDY

This case study is an analysis of the layout of the TTK UAS laboratories and the implementation of LF principles in the new Gene Haas Advanced Machining Lab (*GHAML*). The developed LF must provide the necessary knowledge and skills to the engineers in the I4.0 production system and point out the connections between various modules, configurations, and their impact on the final product. GHML consists of technology, process monitoring sensors, software and connecting links. The production process is described in Fig. 4. The input is product data (drawings, 3D models, BOO), required materials (BOM) and work orders (MRP/MES). The product will be manufactured according to the BOO, and each technological step or operation is reported to the manufacturing execution system (MES). A corresponding CNC program is created for each operation. When all the steps are completed and the quality control is passed, the product is declared ready.

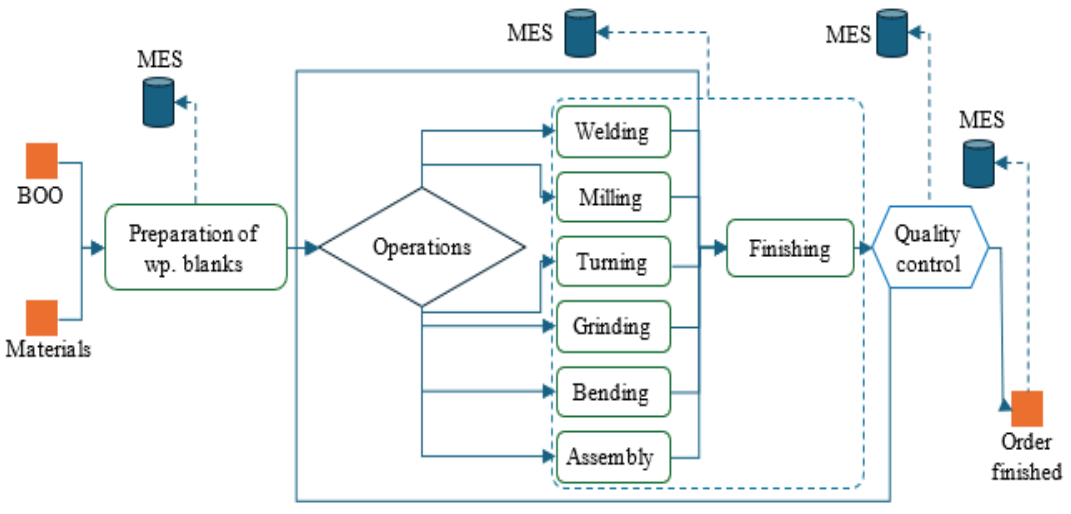


Fig. 4 Production process flow

To implement the production process, it is necessary to perform a manufacturing simulation analysis to determine a reasonable workflow in the production unit. At the beginning of the analysis, it was clear that to fulfil the set goals, the laboratories located in different buildings at the university (measurement laboratory, CAD/CAM classroom, welding and assembly laboratory) must be brought together on one level and location. All the while ensuring that the travel path between laboratories is reasonable. The following were chosen as the objectives of the relocation:

- Aggregation of similar processes and logical sequential arrangement;
- Material flow as linear as possible;
- Common warehousing for materials;
- Quality control in the LF premises;

- Optimisation of travel path lengths and queues;
- Sensors necessary for process monitoring and control;
- Addition of reporting terminals.

A virtual model was created with the help of 3D manufacturing simulation (Fig. 5) software according to the conditions of the university. CNC-machines, industrial robots, other equipment and furniture were inserted in the virtual environment. During the simulation different layouts, as well as machine tending and transport robots were observed [14]. As the last step, using virtual reality technology, all rooms were virtually walked through and adjusted to be comfortable for the person (Fig. 6).

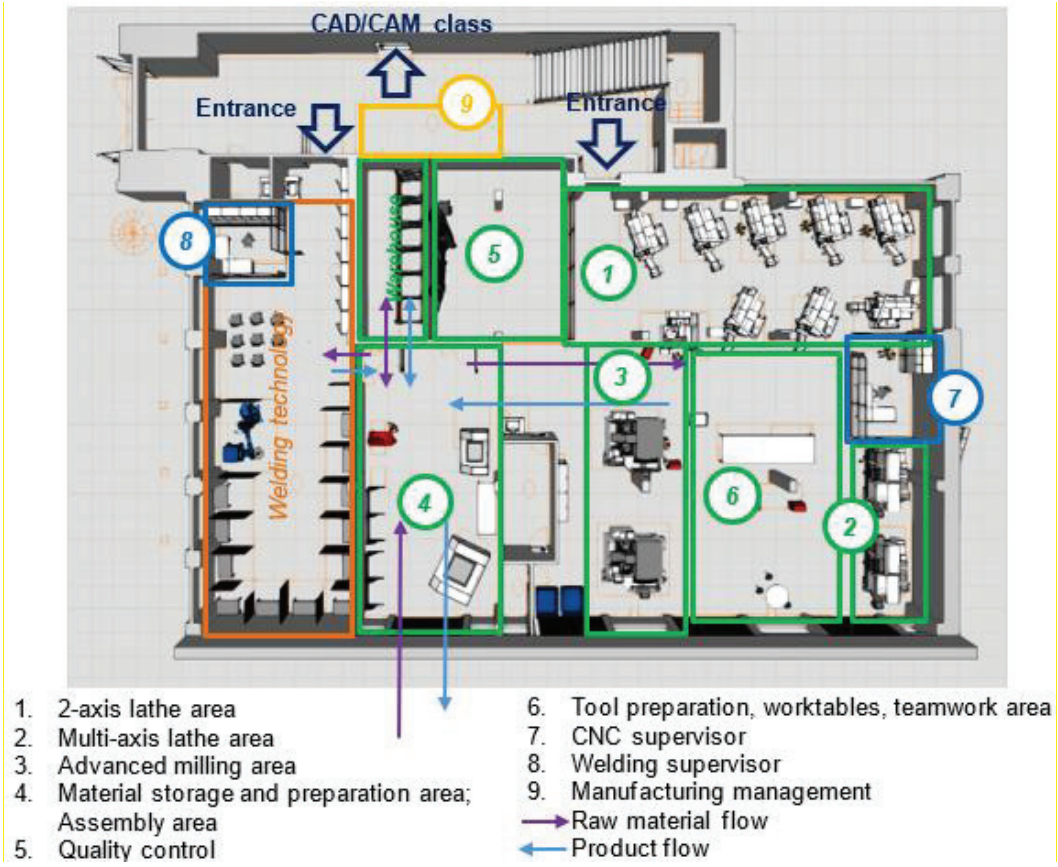


Fig. 5 Gene Haas Advance Machining Lab layout

CNC centres are connected to the MES system using three solutions: Evocon (EC), Global Reader (GR) and Haas WiFi connect (HC). In the case of the first two, spindle on and off times are logged. Logged data is used to calculated the Equipment Overall Effectiveness (OEE) together with parts count reporting. In the case of HC, data logging is broader, including program name, processing speeds and states, among other parameters.

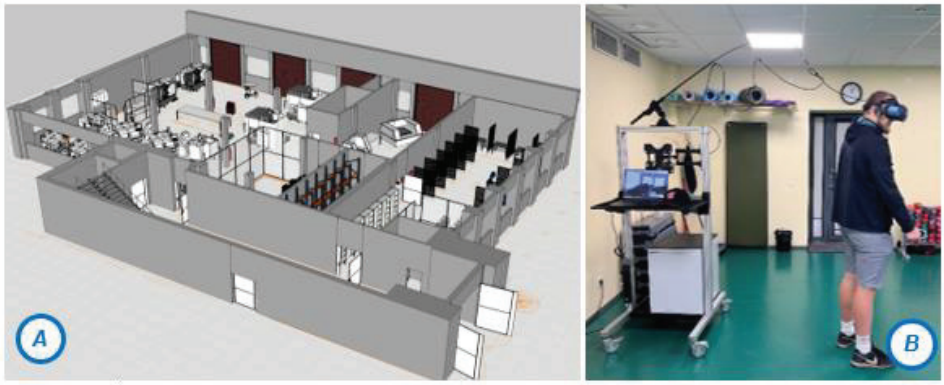


Fig. 6. Validation in virtual reality. A – VR model of the GHML, B – VR walkthrough

5. CONCLUSIONS AND FUTURE WORK

TTK University of Applied Sciences, receiving input from the labour market, professional associations, and entrepreneurs, understood the need to update production technology laboratories. In order to effectively carry out the laboratory development process, a sectoral study had to be conducted, and the characteristic features of a modern teaching laboratory had to be found. A literature review of the LF concept and the pedagogical approach to use in that framework was carried out. Suitable methods and tools were selected, and the Gene Haas Advance Machining Lab learning factory concept was designed and completed during the case study. A list of goals and parameters was drawn up, emphasising sectoral development trends such as adaptive and smart manufacturing systems, VR/AR technologies, human-centred and customer-focused manufacturing, and new directions and developments in pedagogy.

The Psycho-Didactical Model of Engineering Pedagogy was decisive when setting the goals. The application of the model starts with the student, whose prior knowledge is evaluated, and the objectives are set. Hereby, smart production is divided into small operations or workshops, through which the student will gain the necessary prior knowledge to understand the entire production process faster and more effectively. The biggest risks are the integration of different parts and subjects into a single whole and the communication between teaching staff.

Based on the above, a new process was developed, similar to the production process in a manufacturing company but also carrying all the necessary characteristics of the higher education teaching/learning process. The manufacturing process was planned so that similar operations were arranged in a logical sequence and quality control in the middle. Common warehousing for materials used in different operations and material flow as linear as possible, achieving both time and space savings. The proposed solution is unique among Estonian higher education institutions. The developed process was the basis for further analysis. 3D manufacturing simulation and virtual reality software tools were used to perform the analysis. With the new concept, the lengths of the travel path were decreased more than five times. The production flow was optimised for workplaces where queues might occur (sawmills,

measuring devices, computer workplaces), and parallel production capacity was added where necessary. Between areas 4,1 and 6, the mobile industrial robot MIR100 was the best material transport solution. In area 3, the preparation of tools was organised using tool pre-setters and QR codes for information transfer. The following steps will be the renovation and reconstruction of the laboratory premises and the implementation of the above-mentioned results.

For future research, it is necessary to monitor and document how the proposed solution fulfils the originally set goals in real teaching and development. The biggest danger here is the fact that smart manufacturing is a constantly developing concept, and the currently implemented solutions may not be the most effective and sustainable in the long term. Also, we must consider that if there is a major turnaround in SM, it will be quite difficult for the university to meet the investment and research needs. According to this, it is vital to integrate the existing systems, narrow the research field, and offer usable solutions to the local industry.

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REFERENCES

[1] World Economic Forum, 2023, *Future of Jobs Report* 2023, Geneva.
[2] ELLINGRUD K., GUPTA R., SALGUERO J., 2020, *Building The Vital Skills for the Future of Work in Operations*, McKinsey Global Institute.
[3] World Manufacturing Foundation, 2020, *Back to the Future: Manufacturing Beyond COVID-19, Industrial Smart Working*, Milano.
[4] CIMINI C., CAVALIERI S., 2022, *Industrial Smart Working: a Socio-Technical Model for Enabling Successful Implementation*, IFAC-PapersOnLine, 55/2, 505–510.
[5] HAKON D., NINA T., ASSUAD C.S.A., KRISTIAN M., 2023, *A Learning Approach for Future Competencies in Manufacturing Using a Learning Factory*, Procedia CIRP, 118, 1039–1043.
[6] CHELINI J., RICHERT D., 2023, *Teaching Engineering Design for Industry 4.0 Using a Cyber-Physical Learning Factory*, IFAC-PapersOnLine, 56/2, 4699–4704.
[7] FERRARIO A., CONFALONIERI M., BARNI A., GABRIELE I., LANDOLFI G., PEDRAZZOLI P., 2019, *A Multipurpose Small-Scale Smart Factory for Educational and Research Activities*, Procedia Manufacturing, 38, 663–670.
[8] European Factories of the Future Research, 2013, *Factories of the Future Multi Annual Roadmap for the Contractual PPP Under Horizon 2020*, Publications Office of the European Union, Luxembourg.
[9] BAENA F., GUARIN A., MORA J., SAUZA J., RETAT S., 2017, *Learning Factory: the Path to Industry 4.0*, Procedia Manufacturing, 9, 73–80.
[10] MOOR M., VAHER K., RIIVES J., KANGRU T., OTTO T., 2021, *Modern Robot Integrated Manufacturing Cell According to the Needs of Industry 4.0*, Proceedings of the Estonian Academy of Sciences, 70/4, 407–412.
[11] KANGRU T., RIIVES J., MAHMOOD K., OTTO T., 2019, *Suitability Analysis of Using Industrial Robots in Manufacturing*, Proceedings of the Estonian Academy of Sciences, 68/4, 383–388.
[12] RÜÜTMANN T., 2023, *Engineering Pedagogy and Engineering Educators' Competency Model for Effective Teaching and Learning Steam*, Problems of Education in the 21st Century, 81/4, 531–546.
[13] International Society for Engineering Pedagogy, 2023, *Igip Accreditation for Training Centers (Atc) for International Engineering Educators*, IGIP.
[14] KANGRU T., MAHMOOD K., OTTO T., MOOR M., RIIVES J., 2020, *Knowledge-Driven Based Performance Analysis of Robotic Manufacturing Cell for Design Improvement*, in Proceedings of the ASME, USA, Portland.

Appendix 6

Publication VI

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Methodology for Reconfigurable Cobot-Based Quality Control System for SME Production

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***Abstract*—More than a decade ago, we were introduced to the concept of Industry 4.0 (I4.0), and today a lot has been applied in the manufacturing industry. Moreover, the concept of Industry 5.0 (I5.0) is spreading its branches, focusing on collaboration between humans and machines. The continuous development of collaborative robots (cobots) has led to a situation where Small and Medium-sized Enterprises (SMEs) have the financial resources, but lack of knowledge how to integrate these robot systems into their production by the principles of I4.0. The functions of the cobots meet the requirements of SMEs as these are easy to program, lightweight, and universal machines. In this article, we propose a methodology for reconstructing an existing cobot cell into an autonomous quality control system for SME production. This implies the use of Machine Vision (MV) technology with the development of various product databases, and in the future, adapting Machine Learning (ML) functionality. First, the variables are examined and classified by their features, determining their importance in the redesign process. Then, a digital twin model of the robotic system is developed to evaluate the effectiveness and simplify the preliminary programming of the system. This includes technology process-based design for elements such as gripper and multi-position fixture. Finally, we present the assembly and testing of the reconfigurable cobot-based quality control system with test results which imply that the quality control system can perform by the established goals.**

***Keywords*—collaborative robot, machine vision, machine learning, quality control, Small and Medium-sized Enterprise (SMEs) production**

I. Introduction

Industrial companies are using robot solutions in every part of the world to increase throughput, quality and reduce the cost and lack of human labor. According to a Eurofound survey, 39% of European manufacturing companies stated limitations in production due to labor shortages. According to the prediction, made by the United Nations (UN) analysis, we will witness a decrease of 95 million workers from 2015 to 2050 [1]. The demographic effect will accelerate and force even more rapid usage of smart robotic systems. Robot solutions are different in nature: industrial robots, cooperation robots, and specialized autonomous product-based robots adapted to production. Industrial Robots (IRs) are directed at high-volume production and are aimed mainly at large enterprises. Product-based specialized robot systems are also for high-volume production, but on the other hand, lack the flexibility for retuning the Robot Cell (RC), which is important for Small and Medium-sized Enterprises (SMEs). SMEs need to compensate for the lack of labor but still increase the throughput and quality of products. SMEs represent 98% of European manufacturing and mainly produce high-mix low-volume products [2], where the speed of retune and flexibility between different positions in production is essential. Therefore, it is reasonable to implement parts of I4.0 [3] concepts such as Additive manufacturing, Cloud computing, the Internet of Things (IoT), System Simulation, and Integrated Manufacturing [4] etc. to SME manufacturing. Lots of companies are already using these technologies, but it is common to use RC for one application, etc. pick and place. A typical cobot system is equipped with a gripper to move or index products as required. These types of RCs are easy to program, and no high level of knowledge and competence is necessary [5]. The objective of this research is to find methodological ways to develop existing RCs into multi-purpose robotic systems, allowing to maintain the flexibility to react and retune the RC to another position in the production.

For developing a cobot-based quality control system, vision capability must be given to a cobot system to sense and detect objects in an environment. Machine Vision (MV) enables this possibility for a RC. According to the Automated Imaging Association (AIA), machine vision encompasses all industrial and non-industrial applications in which a combination of hardware and software provide operational guidance to devices in the execution of their functions based on the capture and processing of images [6]. The information gathered from MV serves great importance in terms of digitalization and takes robot cells to the next level. In terms of functionality and flexibility, the solution is capable of changing products in SME production quickly. Also, we point out the flexibility and reconfigurability functions of the cobot-based quality control system.

The rest of this paper is organized as follows. Section II presents the proposed framework of cobot unit in SME production. Section III describes the principles of reconfiguration methodology for quality control. Section IV describes the design of cobot-based quality control and its elements. Section V presents the integration of the cobot-based quality control system and reveals the onsite testing. Section VI concentrates on discussion and conclusions, following future work and acknowledgment.

II. Literature Review

A. Collaborative Robot Systems

Collaborative robots are a relatively recent and very active

field of research. Since its advent, the main aim of collaborative robot manufacturers and researchers has been to improve the aspect of human safety during human-robot interaction while increasing the payload capacity of the robot and at the same time maintaining and enhancing the mobility and flexibility in collaborative robots [7]. Collaborative robotics aims to be complementary to such a modern way of doing conventional robotics, increasing the degree of human participation, in terms of shared time and space, and featuring new types of applications or domains [8].

The EU parliament study states that collaborative robotics is the main driver of I4.0 and Europe is the global leader in the supply and implementation of I4.0. The objective of collaborative robotics is to combine the current capabilities provided by robotics, such as effort and precision capacity, with the inherent human skills to make decisions and solve complex problems in inaccurate tasks [9].

Safety is also a topic in any project or research connected with IR-s or collaborative robots. Since 2016, a standard of ISO/TS 15066:2016 was introduced that specifies safety requirements for collaborative and IR systems and work environments [10]. In terms of terminology, Vicentini [11] has presented an overview and developments in this field. According to the EU study, the market for collaborative robots had grown in 2021 by nearly 50% and the forecast for next years shows the range between 20–30% [9]. It is a rapidly developing field in the industry, especially in SMEs. However, currently the cobot market represents only 7.5% of the total robotic market [12].

B. Machine Vision and Learning

Different Machine Vision (MV) systems exist, and these are used for a broad range of applications. The variety of applications use line scan, area scan, and 3D scan cameras and mainly perform presence inspection, measurement, identification, positioning, and defect detection. The vast advantage of MV-based inspection is increased throughput in the detection process. Huang *et al.* [13] improved inspection of glass bottle breakage and contamination. The system developed uses a radial scanning method followed by contour fitting to identify breakage on bottle mouths. The system accomplished an inspection rate of 72,000 bottles per hour while detecting 100% of defective bottles and mislabeling 0.297% of bottles [14]. Kinell *et al.* [15] presented the 3D vision mounted to IR in their research "Autonomous metrology for robot mounted 3D vision systems". A viewpoint selection algorithm was developed to locate objects using cloud data. Useful viewpoints are ranked by algorithm, providing necessary positions where to position the camera. Alonso *et al.* [16] presents an overview of two methods to inspect welding seams. First, they use a 3D vision sensor to acquire a cloud point dataset, and second, a laser-based method, measuring weld bead dimensions and acquisition data using depth.

Machine Learning (ML) concerns the construction and study of systems that can automatically learn patterns from data. Models built with ML can be used for prediction, performance optimization, defect detection, classification, regression, or forecasting [17]. Razvi *et al.* [18] presents a detailed overview of ML applications throughout the AM design-to-product transformation cycle. Different ML methods are discussed to find well-suited solutions to problems.

C. Reconfiguration Methodology

As the nomenclature in manufacturing is rapidly changing and technical solutions are developing continuously, companies are required to upgrade their production systems. The system must have a feature for simple reconfiguration or even a redesign option for quality control cell improvements. Yim *et al.* [19] introduced three subtypes of modularity in product design: slot architecture, bus architecture and sectional architecture. In slot architecture, each of the interfaces between components is a different type, the various components in the product cannot be interchanged. For example, the robot arm which has rigid links, motors, transmission, and sensors. In bus architecture, a common feature is that the other physical components connect via the same type of interface. A laptop with USB ports, for example, modular elements can be added or reconfigured. In sectional architecture, all interfaces are of the same type, and there is no single element to which all the other components attach, there is no base component [20]. In our research, we are using the principles of slot and bus architecture for the reconfiguration of existing robot cell for quality control system.

The advantage of a reconfigurable system is evident from its evolvability, multifunction, and survivability. The changing environment, in terms of product and production, forces us to keep an open mind for additional development of existing systems. Kalimuthu *et al.* [21] introduced research on a reconfigurable robot which is capable of expanding and collapsing its dimensions to adapt environment. Paramasivam *et al.* [22] have discussed an overview of general reconfiguration methodology, using classification for subtopics such as manufacturing, environment, assembly, safety, and reliability. On the other hand, Gualtieri et al. have developed a multicriteria methodology for evaluating the conversion of manual assembly workstations into collaborative human-robot work cells. The research mentioned above supports the background for our study and using its elements, we have adapted the reconfiguration principles for developing a cobot-based quality control system.

III. The Framework of Cobot Unit in SME Production

The cooperative company's main products are in the field of IoT and focus on zero-emission small vehicles like e-bikes and e-scooters and their components. This SME has a high product variation of similar products. Also, the procedures of manufacturing a single product are complex and consist of highly automated manufacturing lines for producing assembled circuit boards and on the other hand, manual labor for soldering soft and delicate cables for enabling functionality between different parts of the product. Quality control is carried out throughout production and multiple positions between different processes. We are focusing on the cobot quality control unit in our research which is illustrated in Fig. 1 and the RC will be added into production. Currently, the quality test position is manual. No data is preserved about the number and reasons for defects. In terms of reconfiguration of existing RC to a cobot-based quality

system, it is important to evaluate the environment, manual workplace, and processes and workflow. A subparagraph Human-robot collaboration and environment is dedicated to different methods of evaluation.

As a manufacturing SME, the enterprise uses a multidimensional production system, where they have full control, starting with the product and manufacturing design, and quality and ending the chain with support, as shown in Fig. 2. That enables the freedom of making changes in production but also sets the constraints.

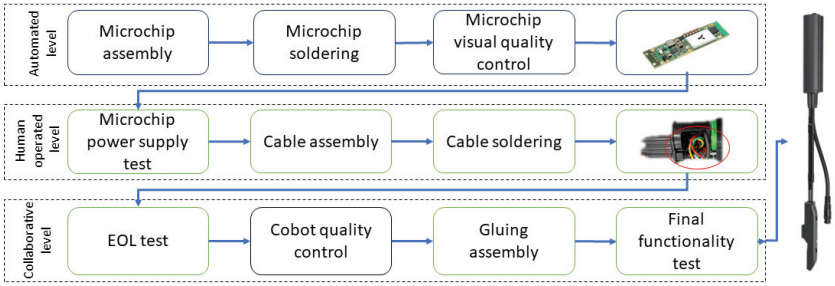


Fig. 1. Typical SME production levels.



Fig. 2. Multidimensional production of SME.

A. Human-Robot Collaboration and Environment

According to Rauch *et al.* [23], part of manufacturing SMEs do not have knowledge and skills about the implementation of collaborative robots even if experts in the field believe that it will be an important technology for the growth of their business. A similar approach extends to the enterprise we are doing our research. There is knowledge of product and manufacturing design, but a lack of competence in integration of collaborative robots. The Human-Robot Activity Allocation procedure is a fundamental part of the conversion process. Starting from an existing manual assembly workstation, this procedure allows for the separation of tasks and activities between the operators and robots by considering the influence of different production indexes concerning technical feasibility, safety and ergonomics, process quality and economic aspects [24]. Here is a list of related research presented which is applied to the topic. Kangru [25] has developed an optimization of the decision-making process in industrial robot selection based on Key Performance Indicators (KPIs) and a Decision Support System (DSS). Haydaryan [26], on the other hand, has developed a hierarchy decision-making method for the human-robot task analysis based on productivity, human fatigue, safety, and quality evaluation criteria. Cencen [27] have proposed a human-robot coproduction design methodology to overcome the challenges faced in the SME context [24]. All these approaches support SMEs in focusing on important topics while being in the starting position of implementing a cobot system into production or reconfiguring an existing cell.

The quality control process involves three areas: input area, process area and output area shown in Fig. 3. The input area is for stacking various products by human operators to be ready for control. The process area is the most complicated in the RC. It involves picking up the product, which is an IoT module, one at a time, taking the product into a robot-controlled fixture, opening the product, detecting the product model, multi-position vision processes, closing the product, and taking it to the output area. The output area is divided into two: finished products and defective products. The defects are divided into categories according to the defect type for repair or utilization.

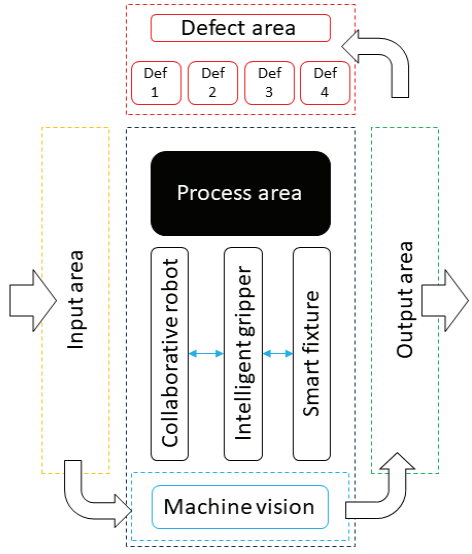


Fig. 3. The concept of redesigend RC for quality control.

The environment in SME production sets limitations and constraints to the layout. The biggest factors are floor space, production workflow and Human-Robot Collaboration

(HRC). The floor space sets definite boundaries for cobot system size and offers irregular shaped space for the floor plan. A rectangular shape of 2.1 m by 2.6 m, where a triangle of size 1.0 m by 1.5 m is cut away. In terms of any development project involving industrial or collaborative robots, this is one of the essential constraints to be focused on.

Flow production is a manufacturing process that is defined by the continuous 'flow' of goods along an assembly line. The goods are put through different stages on the assembly line before being packaged for delivery to the end customer [28]. Production workflow sets the location of the developed cobot system between different processes inside SME production. This feature is directly connected to the floor space and usually influences each other. In our research, the quality control cobot system is planned between the End-of-Line (EOL) testing and glueing process. The importance of the quality of information in this point is essential. Validated products are sealed waterproof in the next process flow of glueing, making it impossible to reopen the product to repair any defects.

The third important topic to consider is HRC and interaction in the developed system which we create a third, collaborative level, in SME production. HRC is expected to increase the quality rate and performance efficiency [29], which is divided into a variety of aspects, safety, regulations, technical potential, and ergonomics, as stated above. A changed environment needs preventive training and a test period. Afterwards, analysis can be carried out to make changes in HRC, if necessary. The following model in Fig. 4, presented by Oberc [30] can be observed and followed by management of SME to execute the training period, followed by analysis.

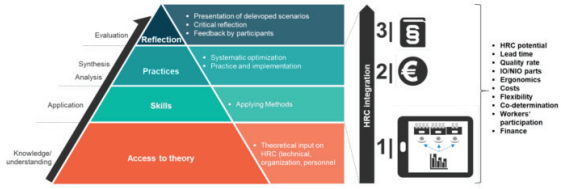


Fig 4 HRC training cycles [30].

B. The product

The following subchapter presents the importance of the product and why it is necessary to analyze it. The product can be characterized by many features such as size, shape, color, weight, material, part or assembly, soft and rigid elements, quantity etc. In terms of redesigning a system, it is essential to evaluate the features that affect the system the most. Paramasivam [22] has presented a combination and methods in his research for design which can be used in the redesigning process of a system. One of the steps in general methodology, in the paper, stated above, is adapting the Product design Evaluation Matrix (PEM) which will be a M × M matrix. In this paper, we suggest a simplified scheme of using features in columns and effects in a row for quick evaluation for use in SMEs. The product-based features and effects are presented in the table below Table 1.

Table 1. Simplified evaluation of product features

Feature/Affect	No affect	Small	Moderate	Vast
Size				x
Shape				x
Color	x			
Weight			x	
Material		x		
Part/assembly			x	
Quantity		x		
Soft/rigid elements				x

The product for this research, as stated above in A, is an IoT module. Using the information from Table 1, the most important features are size, shape and soft/rigid elements which are followed by weight and part or assembly features. In terms of size, the product has an irregular shape and length-to-diameter ratio which makes it challenging to handle with a cobot system. The product is a complex assembly, consisting of shell-type elements, cables, connectors, circuit board assembly, and battery. This type of assembly is not commonly presented in pick-and-place assignments for cobot systems. Fig. 5 presents the shape and size of the IoT module assembly. The limitations set by the product features are essential for reconfiguring any industrial or cooperative robot cell.

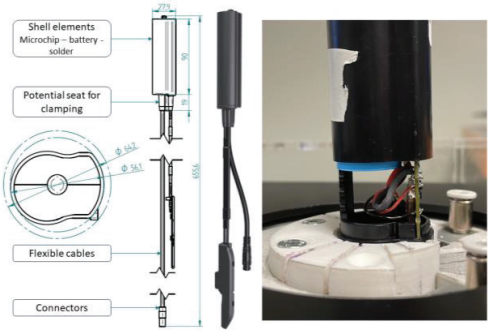


Fig. 5. The product's size and shape.

IV. Reconfiguration Methodology and Design of Cobot Based Quality Control Cell

The information gathered in previous paragraphs is the key feature of reconfiguring the collaborative robot cell into a robot-based quality control system. In this phase of our research, we focus on the necessary reconfigurations and redesign steps needed to be executed. Also, the aspect of constraints is being considered.

A. Existing Robot Cell

Considering the constraints and features of the product and floor space, they must fit the requirements, but also fulfill all the functions. The collaborative robot reach area starts from 500 mm and ends around 1800 mm. The suitable collaborative robot must, at minimum, stay in the mid-range of stated values. Most collaborative robots can be mounted to the wall, table, and ceiling. In terms of height, concentrating on the product length Fig. 5, the robot must be mounted to the height of 1000 mm at least for clearance to the cables. From the point of view of ergonomics, input and output area is defined with average operator height, for loading and unloading of the products. In this paper, we have used a

collaborative robot Omron TM5-900 with a reach of 900 mm. The controller allows the usage of 16 digital inputs and outputs, 2 analogue inputs and 1 output for I/O ports. Communication can be established using RS232, Ethernet or Modbus Transmission Control Protocol (TCP)/Remote Terminal Unit (RTU) which is important for equipment added to the system [31]. As a common solution, this existing robot cell uses a modular aluminum profile frame with the possibility to add modular features with low time consumption, but high precision and rigidness.

B. The Principle of Smart Fixture

The product always sets several limitations for the fixture. In this research, the crucial feature of the product is the sequence of cables which are in two rows shown in Fig 5. These cables ensure the functionality of the product. Due to the variety of similar products in SMEs, the detection by MV of the present product model is also one of the key features. Therefore, the smart fixture must ensure two positions for MV detection, from both sides of the product.

The principle of smart fixture is divided into three positions, shown in Fig. 6: Clamping Process (CP), Quality Control Process (QCP) and Unclamping Process (UNP). The clamping process is described as follows: the cobot places the product in the fixture, the fixture clamps the product for a stable and accurate position, and then the cobot opens the product to reveal the important area inside the product. All the communication is executed through the cobot system controller. Secondly, the quality control unit actions can be described as detection of the model, checking the first-row cables of the product, fixture rotation to position 2, checking the second-row cable sequence by color and finally fixture rotation back to position 1.

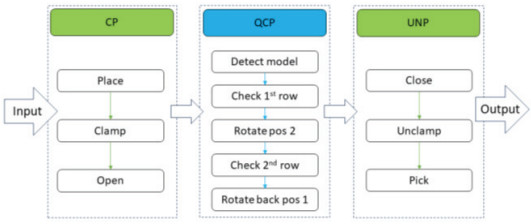


Fig. 6. The principle of smart fixture.

C. The Design of Fixture and Additive Manufacturing Techniques

As the principle of smart fixture is presented above in Section IV.B, the technical design and additive manufacturing techniques are discussed in the following subparagraph. Several versions of the design were discussed, here we present the final version of the smart fixture. The same approach has been used for the frame, as used in the frame of the existing robot cell, the modular aluminum profile. The frame supports the base plate which has a V-shaped opening for inserting the long product with flexible cables.

The limitations foresee the use of two positions of the product for quality control. Only the start and end position of the rotational axis is determined. With the start position of 0° and the end position of 180°, no other position is relevant in this case. The motion of the product could be achieved using a step motor, servo motor or rotary cylinder. With no need to determine specific degrees in the rotational axis, we have used a pneumatical rotational cylinder with electric control through cobot control. One of the benefits of the cylinder is adjustable acceleration and deceleration speed which ensures the smooth positioning of the product inside the fixture. The usage of spur gears allows to relocation of the rotational position. One of the gears has a similar V-shaped opening, as the base plate, creating access for the product. That gear has a groove on the bottom, allowing bearings to guide the rotation. A guide plate supports the gear from below of bearings. On top of the gear, there are pockets for pneumatic cylinders. These cylinders apply the force of 10 N to clamp the product inside the modular insert. The modular insert is designed according to the shape limitations of the product and bolted to the gear. In terms of manufacturing, the design of insert and spur gears, additive manufacturing [17, 32] principles are followed. This gives the freedom of creating sharp corners, pockets inside closed solid bodies and complex geometry, such as narrow slots inside insert for making it a flexible body on one side. The moving parts of the fixture are protected with the side and top plate for safety, as shown on the right side of Fig. 7.

On the left side of Fig. 7 is located the machine vision unit for quality control. For image quality and focus adjustment, it is assembled on a guide assembly and bolted together with a camera mount. It allows manual adjustment for focus. In this research, we use a 2D-vision system, In-Sight 7905C from Cognex.

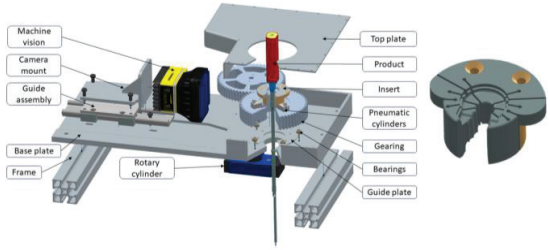


Fig. 7. The modular assembly of smart fixture and product insert.

V. Integration and Onsite Test

This paragraph presents the overview of the integration and testing of the reconfigured cobot-based quality control system. Our research presents the preliminary results of this application. Furthermore, continuous development and testing in the SME of the system will be done according to the preliminary results.

The quality control module, shown in Fig. 8, is assembled to the process area, shown in Fig. 3, using an aluminum profile solution. Then, the stacking shelves are added to create an input and output area for the products. The programming of the system consists of multiple layers where the main program controls the subprograms, MV unit and smart fixture. For creating the multi-layer programming, following the structure of the system concept, shown in Fig. 3, and smart figure processes shown in Fig. 6, allow efficient architecture for programming. For example, inside the input area, the positions of the products are described as variables and the detection is done by a force feedback gripper. This allows RC to cope with the changing

environment in production, where all the product slots must not be sequentially fulfilled with products. A similar approach is used in the output area, where the cobot divides the products into different areas, using a preliminary programmed ratio between OK and NOK products.

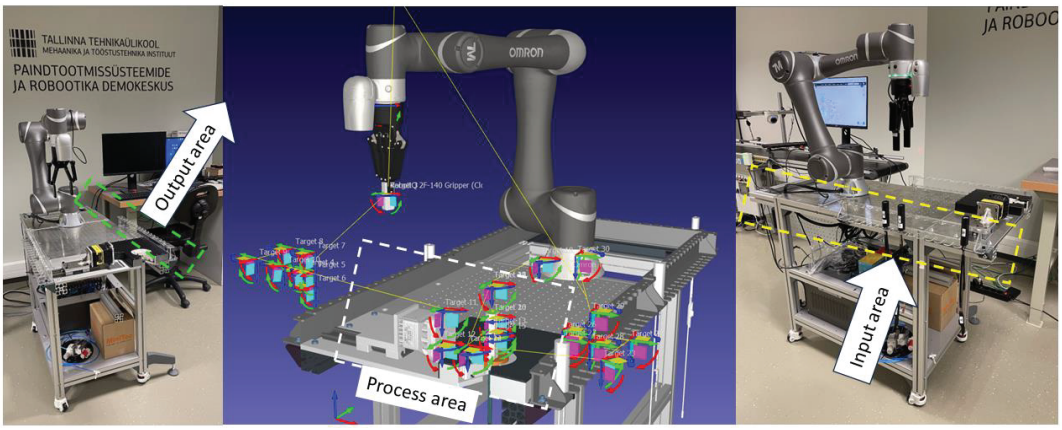


Fig. 8. Virtual and real cobot based quality control system.

The importance of smart fixture positioning precision is essential in the quality inspection process. The MV camera detection is based on the location, size and color of the specific area of the product, where the cables are connected to. The lighting, focus area and size, and background are important properties for successful detection. As shown in Fig. 9, the image presents the areas for specific products and important areas inside the product. On the left side of Fig. 9, green boxes represent the successful detection of cables by their color and sequence. This means the functions of the product are correct and the product can move to the next process in the production. While the right side of the figure represents the failed detection of the cables, this means that the product is defective and is moved to the defect area. In the example, the product has failed all the detection areas out of three. In terms of any failed feature, the product is classified as a defective product. The following steps are required to repair the product and test it again in the quality control unit.

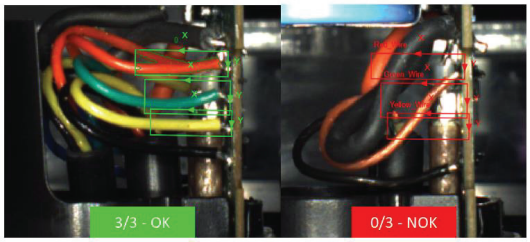


Fig. 9. Machine vision testing OK-NOK.

Conclusively, the preliminary testing has been successful using different products from SME production. The cobot-based quality control system is capable of detecting correct and defective products and separating them. In terms of cycle time, we tested the cobot-based system at various speed rates. Using a 10% application speed for the robot, the cycle time was 90 s. While, using 90% of the movement speed, the cycle time was 50 s. We suggest that the motion speed should stay in the range of 250 to 500 mm/s. This constraint is connected to the dynamics of the product. In terms of MV, the detection process varies from the number of objects being tested. For example, the detection of four objects took a time of 200 ms for one side of the product. In terms of the smart fixture, the clamping and rotation of the product took two seconds to rotate the product 180°. It is easily possible to adjust the rotation speed, but the sustainability of the quality control process is far more important. Finally, the results of the presented cobot-based quality control system show that the application is capable of detecting defective products effectively. Further testing will be carried out to check the sustainability of the system.

VI. Discussion and Conclusion

In this study, the importance of reconfiguration methodology for quality control systems has been discussed. The implementation of the cobot-based system in SME production is a productive way to increase precision and preserve data for future analysis and predictions inside the production. Reconfiguring methodology discusses the essential features such as environment, product, and existing robot cell for executing the redesign process in low time consumption.

In the practical use case, using the presented methodology, an existing cobot cell was reconfigured into a quality control system to check the cable sequence of a product and differentiate defective products by their fault. The quality module can be easily detached from the current cobot and used otherwise. Moreover, in the future, we will carry out testing the system in real production for reliability, precision, and data transfer. Developments such as the implementation of Electronic Shelf Labels (ESL) allow output to adapt according to defect type and sequence and make predictions about error sequences in previous processes.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

MM and MS conducted the research and the development

project of this cobot based quality control system; TO and JR analyzed the data that was generated using virtual environment tools; MM, and JMV wrote the paper. All authors had approved the final version of this article.

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References

[1] D. Davis. (2022). The IX Network, a division of IQPC. *Industrial Transformation*. [Online]. Available: https://www.industrialtransformationnetwork.com/personal-process-safety/articles/addressing-europes-manufacturing-worker-shortage

[2] S. Pieskä, J. Kaarela, and J. Mäkelä, "Simulation and programming experiences of collaborative robots for small-scale manufacturing," in *Proc. 2018 2nd International Symposium on Small-scale Intelligent Manufacturing Systems (SIMS)*, Cavan, Ireland, 2018, pp. 1–4. https://doi.org/10.1109/SIMS.2018.8355303

[3] R. S. Batth, A. Nayyar, and A. Nagpal, "Internet of robotic things: Driving intelligent robotics of future-concept, architecture, applications and technologies," in *Proc. 2018 4th International Conference on Computing Sciences (ICCS)*, Jalandhar, 2018, pp. 151–160. https://doi.org/10.1109/ICCS.2018.00033

[4] M. Moor, K. Vaher, J. Riives, T. Kangru, and T. Otto, "Modern robot integrated manufacturing cell according to the needs of Industry 4.0," in *Proc. the Estonian Academy of Sciences*, Tallinn, 2021, pp. 407–412. https://doi.org/10.1088/1757-899X/1140/1/012034

[5] X. Yang, Z. Zhou, J. H. Sørensen, C. B. Christensen, M. Ünalan, and X. Zhang, "Automation of SME production with a cobot system powered by learning-based vision," *Robotics and Computer-Integrated Manufacturing*, vol. 83, 102564, 2023. https://doi.org/10.1016/j.rcim.2023.102564.

[6] T. Allen. (2020). What is machine vision? Everything you need to know. [Online]. Available: https://aijourn.com/what-is-machine-vision-everything-you-need-to-know/

[7] F. Sherwani, M. M. Asad, and B. S. K. K. Ibrahim, "Collaborative robots and Industrial Revolution 4.0 (IR 4.0)," in *Proc. 2020 International Conference on Emerging Trends in Smart Technologies (ICETST)*, IEEE, 2020. https://doi.org/10.1109/ICETST49965.2020.9080724

[8] F. Vicentini, "Collaborative robotics: A survey," *Journal of Mechanical Design*, vol. 143, no. 4, 040802, 2021. https://doi.org/10.1115/1.4046238

[9] E. Gambao. (2023). Analysis exploring risks and opportunities linked to the use of collaborative industrial robots in Europe. [Online]. Available: https://www.europarl.europa.eu/RegData/etudes/STUD/2023/740259/EPRS_STU(2023)740259_EN.pdf

[10] ISO/TS 15066. (2016). Robots and Robotic Devices—Collaborative Robots. ISO standard. [Online]. Available: https://www.iso.org/standard/62996.html

[11] F. Vicentini, "Terminology in safety of collaborative robotics," *Robotics and Computer-Integrated Manufacturing*, vol. 63, 101921, 2020. https://doi.org/10.1016/j.rcim.2019.101921

[12] International Federation of Robotics. (2023). Industrial Robots—Definition. [Online]. Available: https://ifr.org/industrial-robots

[13] B. Huang *et al.*, "Research and implementation of machine vision technologies for empty bottle inspection systems," *Engineering Science and Technology, an International Journal*, vol. 21, no. 1, pp. 159–169, 2018. https://doi.org/10.1016/j.jestch.2018.01.004

[14] A. Akundi and M. Reyna, "A machine vision based automated quality control system for product dimensional analysis," *Procedia Computer Science*, vol. 185, pp. 127–134, 2021. https://doi.org/10.1016/j.procs.2021.05.014

[15] P. Kinnell *et al.*, "Autonomous metrology for robot mounted 3D vision systems," *CIRP Annals*, vol. 66, no. 1, pp. 483–486, 2017. https://doi.org/10.1016/j.cirp.2017.04.069

[16] V. Alonso *et al.*, "Industry 4.0 implications in machine vision metrology: An overview," *Procedia Manufacturing*, vol. 41, pp. 359–366, 2019. https://doi.org/10.1016/j.promfg.2019.09.020

[17] T. Wuest *et al.*, "Machine learning in manufacturing: Advantages, challenges, and applications," *Production & Manufacturing Research*, vol. 4, no. 1, pp. 23–45, 2016. https://doi.org/10.1080/21693277.2016.1192517

[18] S. S. Razvi *et al.*, "A review of machine learning applications in additive manufacturing," in *Proc. International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, 2019, vol. 59179. https://doi.org/10.1115/DETC2019-98415

[19] M. Yim, D. G. Duff, and K. D. Roufas, "PolyBot: A modular reconfigurable robot," in *Proc. IEEE International Conference on Robotics and Automation*, ICRA 2000, Millennium Conference, IEEE, 2000, vol. 1. https://doi.org/10.1109/ROBOT.2000.844106

[20] J. Seo, J. Paik, and M. Yim, "Modular reconfigurable robotics," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 2, pp. 63–88, 2019. https://doi.org/10.1146/annurev-control-053018-023834

[21] M. Kalimuthu *et al.*, "Transformation design principles as enablers for designing reconfigurable robots," in *Proc. International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers, 2021, vol. 85420. https://doi.org/10.1115/DETC2021-69373

[22] V. Paramasivam and V. Senthil, "Analysis and evaluation of product design through design aspects using digraph and matrix approach," *Int. J. Interact. Des. Manuf.*, vol. 3, pp. 13–23, 2009. https://doi.org/10.1007/s12008-009-0057-9

[23] E. Rauch, T. Stecher, M. Unterhofer, P. Dallasega, and D. T. Matt, "Suitability of Industry 4.0 concepts for small and medium sized enterprises: Comparison between an expert survey and a user survey," in *Proc. the International Conference on Industrial Engineering and Operations Management*, Bangkok, Thailand, 2019.

[24] L. Gualtieria, E. Raucha, R. Vidonia, and D. T. Matta. "An evaluation methodology for the conversion of manual assembly systems into human-robot collaborative workcells," *Procedia Manufacturing*, vol. 38, pp. 358–366, 2019. https://doi.org/10.1016/j.promfg.2020.01.046

[25] T. Kangru, J. Riives, T. Otto, V. Kuts, and M. Moor, "Optimisation of decision-making process in industrial robot selection," *Journal of Machine Engineering*, vol. 20, no. 1, pp. 70–81, 2020. https://doi.org/10.36897/jme/117788

[26] S. Heydaryan, J. S. Bedolla, and G. S. Belingardi, "Design and development of a human-robot collaboration assembly process in the automotive industry," *Appl. Sci.*, vol. 8, no. 344, 2018. https://doi.org/10.3390/app8030344

[27] A. Cencen, J. C. Verlinden, and J. M. P. Geraedts, "Design methodology to improve human-robot coproduction in small- and medium-sized enterprises," *IEEE/ASME Transactions on Mechatronics*, vol. 23, no. 3, pp. 1092–1102, June 2018. https://doi.org/10.1109/TMECH.2018.2839357

[28] A. Bland. (2022). What is Flow Production—And Can SMEs Use it? [Online]. Available: https://www.unleashedsoftware.com/blog/what-is-flow-production-and-can-smes-use-it

[29] B. Vallespir and T. Alix, *Advances in Production Management Systems, New Challenges, New Approaches*, No. AICT-338, Springer, 2010.

[30] H. Oberc *et al.*, "Human robot interaction–learning how to integrate collaborative robots into manual assembly lines," *Procedia Manufacturing*, vol. 31, pp. 26–31, 2019. https://doi.org/10.1016/j.promfg.2019.03.005

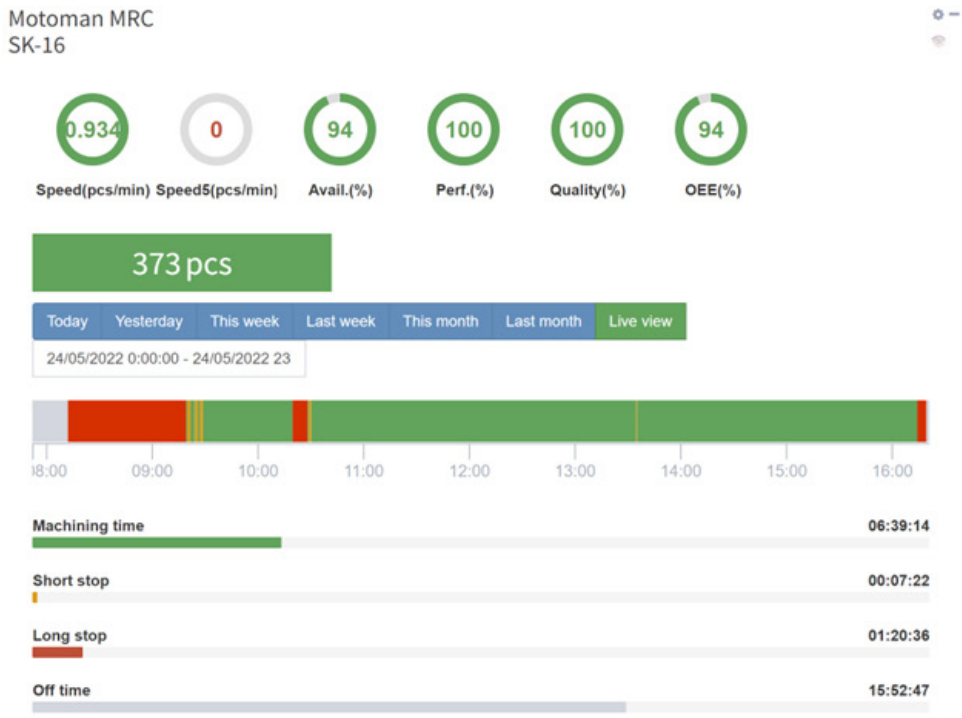
[31] Omron. (2023). TM series specifications. [Online]. Available: https://www.ia.omron.com/products/family/3739/specification.html

[32] B. Berman, "3-D printing: The new industrial revolution," *Business Horizons*, vol. 55, no. 2, pp. 155–162, 2012. https://doi.org/10.1016/j.bushor.2011.11.003

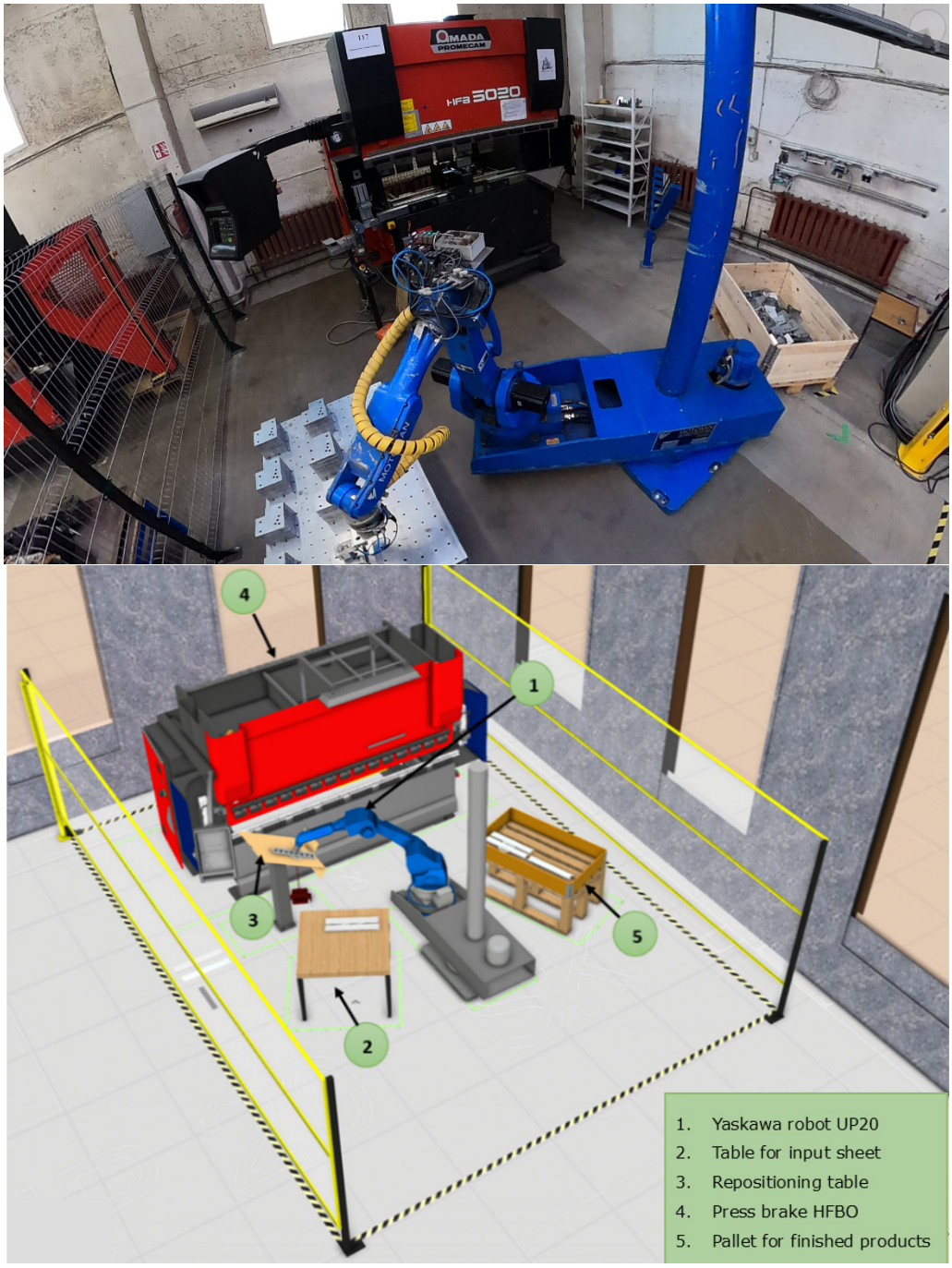
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Appendix 7 – Production Dashboard Overview





Appendix 8 – Real and Virtual Robot Workplace



Curriculum vitae

Personal data

Name:	Madis Moor
Date of birth:	April 28, 1990
Place of birth:	Rakvere, Estonia
Citizenship:	Estonian

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Education

2020–2026	Tallinn University of Technology, School of Engineering, Production Engineering and Robotics, PhD studies
2013–2016	Tallinn University of Technology, Institute of Mechanical and Industrial Engineering, Product Development and Production Engineering, MSC
2009–2013	TTK University of Applied Sciences, Mechanical Engineering
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Language competence

Estonian	Native speaker
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Professional employment

2024 –	TTK University of Applied Sciences, Institute of Technology, Lecturer, Coordinator of Mechanical Engineering
2020 –	Tallinn University of Technology, Faculty of Engineering, Department of Mechanical and Industrial Engineering, PhD student-junior researcher
2016 –	Toucan Engineering OÜ, Development engineer
2023 – 2024	Tallinn University of Technology, Faculty of Engineering, Project manager (0,75)
2021 – 2022	IMECC OÜ, Development engineer (0,50)
2019 – 2022	Tallinn Industrial Education Centre, Senior development engineer (0,5)
2017 – 2023	TTK University of Applied Sciences, Institute of Technology, Lecturer
2013 – 2016	TTK University of Applied Sciences, Faculty of Mechanical Engineering, Assistant
2011 – 2013	TTK University of Applied Sciences, Faculty of Mechanical Engineering, Laboratory engineer (0,5)

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

Defended theses

- 2016, Development of High-Speed Robotic Milling System in TUT, MSc, Supervisor Martinš Sarkans, Tallinn University of Technology, Institute of Mechanical and Industrial Engineering, Product Development and Production Engineering.
- 2013, Design and Manufacturing Technology of a CNC Lathe Workpiece Feeding Device, BSc, Supervisor Tavo Kangru, TTK University of Applied Sciences, Faculty of Mechanical Engineering.

Scientific work
Publications

1. Kangru, T., Moor, M., Rudz, A., & Jänes, A. (2024). Reconstructing a Manufacturing Laboratory to a Learning Factory: a TTK UAS Case Study. Journal of Machine Engineering, 24(3), 133-140.
2. Moor, M., Sarkans, M., Riives, J., Otto, T., Vano, J.-M. (2024). Methodology for reconfigurable cobot-based quality control system for SME production. International Journal of Engineering and Technology (IJET), 16 (2), 113−119. DOI: 10.7763/IJET.2024.V16.1265.
3. Moor, M., Pakkanen, J., Raamets, T., Mahmood, K., & Riives, J. (2024, January). Industrial data analytics in manufacturing shop floor level. In AIP Conference Proceedings (Vol. 2989, No. 1, p. 030006). AIP Publishing LLC.
4. Moor, M., Sarkans, M., Kangru, T., Otto, T., & Riives, J. (2024). AI functionalities in cobot-based manufacturing for performance improvement in quality control application. Journal of Machine Engineering, 24(2), 44-55.
5. Moor, M., Vaher, K., Riives, J., Kangru, T., & Otto, T. (2021, May). Modern Robot Integrated Manufacturing Cell According to the Needs of Industry 4.0. In IOP Conference Series: Materials Science and Engineering (Vol. 1140, No. 1, p. 012034). IOP Publishing.
6. Kangru, T., Mahmood, K., Otto, T., Moor, M., & Riives, J. (2020, November). Knowledge-Driven Based Performance Analysis of Robotic Manufacturing Cell for Design Improvement. In ASME International Mechanical Engineering Congress and Exposition (Vol. 84539, p. V006T06A032). American Society of Mechanical Engineers.
7. 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.

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2009–2013	Tallinna Tehnikakõrgkool, Mehaanika teaduskond, Masinaehituse õppetool, BSC
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2024 –	Tallinna Tehnikakõrgkool, Tehnikainstituut, Lektor, Masinaehituse õppekava juht
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2016 –	Toucan Engineering OÜ, Arendusinsener
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