DOCTORAL THESIS

Reconfigurable Manufacturing Based on Autonomously Moving Collaborative Robot Solutions

Kristo Vaher

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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.

Kristo Vaher

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signature

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Autonoomselt teisaldataval koostööroboti lahendusel põhinev ümberseadistatav tootmine

KRISTO VAHER

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List of publications

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

I. 3.4 **Vaher, K.**; Vainola, V.; Otto, T. (2019). Industry 4.0 Laboratory. IV International Scientific Conference, Industry 4.0. Summer session, 52–53. volume 1/5 06.2019, Burgas, Bulgaria, https://www.etis.ee/Portal/Publications/Display/9ef9e1fb-2c2e-4b86-9fc5-9ccb8f80ca60

II. 3.1 **Vaher, K**.; Kangru, T.; Otto, T.; Riives, J. (2019). The mobility of robotised work cells in manufacturing. 30th International DAAAM Symposium ''Intelligent Manufacturing & Automation'', 23-26th October 2019, Zadar, Croatia, https://www.etis.ee/Portal/Publications/Display/fe90f577-90cb-4b03-a7e5-0a97346f646d

III. 1.1 **Vaher, K**.; Otto, T.; Riives, J. (2020). Positioning error correction of autonomously movable robot arm. Journal of Machine Engineering 2020; 20(4):152–160, https://www.etis.ee/Portal/Publications/Display/3bce1ee4-3536-422f-823f-9b996f1f188a

IV. 1.1 **Vaher, K.**; Mahmood, K.; Otto, T.; Riives, J. (2021). Simulation based feasibility analysis of autonomously movable robot arm. Proceedings of the Estonian Academy of Sciences, 70 (4), 422−428. https://www.etis.ee/Portal/Publications/Display/0f9109d2-0a20-4e09-984d-ad8fad9b377a

V. 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. https://www.etis.ee/Portal/Publications/Display/41091f1c-7386-4060-8f37-c9b50f043799.

Copies of the publications constituting the thesis are included in the appendix and marked in the text in Roman numbers as presented above.

Author's Contribution

I The author has developed the concept and methodology of the study, collected background information and data, analyzed the data, and synthesized the results, made conclusions, and composed the paper, with help from Vello Vainola. The overall study was supervised by Tauno Otto. The author presented the paper at the IV International Scientific Conference, "Industry 4.0. Summer session" on June 25 to 27, 2019 in Burgas, Bulgaria.

II The author has developed the concept and methodology of the study, collected background information and data, analyzed the data, and synthesized the results, made conclusions, and composed the paper in consultation with Tavo Kangru. The overall study was supervised by Tauno Otto and Jüri Riives. The author presented the paper at the 30nd DAAAM International Symposium conference "Intelligent Manufacturing & Automation" on October 23 to 25, 2019 in Zadar, Croatia.

III The author has developed the concept and methodology of the background information and data, analyzed the data, and synthesized the results, made conclusions, and composed the paper. The overall study was supervised by Tauno Otto and Jüri Riives. The author presented the paper at the XXXI CIRP Sponsored Conference on "Supervising and Diagnostics of Machining Systems" March 8 to 12, 2020 in Karpacz, Poland.

IV The author has developed the concept and methodology of the study, collected background information and data, analyzed the data, carrying out the case study, and synthesized the results with help from Kashif Mahmood, made conclusions, and composed the original manuscript, which was reviewed by Tauno Otto and Jüri Riives. to publish in the scientific journal's "Manufacturing Engineering" Proceedings of the Estonian Academy of Sciences in 2021.

V The co-author developed the concept and methodology of the technological system for the Industry 4.0 laboratory and built it for practical tests presented in Chapter IV "Integrated Manufacturing Implementation". The concept and methodology of the study was developed by Madis Moor and Jüri Riives. Madis Moor collected background information and data, analyzed the data, synthesized the results, made conclusions, and composed the draft paper, which was reviewed by Tauno Otto and Jüri Riives, to publish in the scientific journal's "Manufacturing Engineering" Proceedings of the Estonian Academy of Sciences in 2021.

Introduction

Robotization has been a prominent topic in the industrial sector for quite some time. However, the widespread adoption of robots in manufacturing companies is still limited. One of the critical challenges in implementing industrial robots is determining whether robotization is suitable for a company, considering the availability of sufficient workload. This issue becomes particularly significant for small and medium-sized enterprises (SMEs) where there may not be enough workload in a single specific location to justify investing in a robot. To address this challenge, production processes can be reorganized to distribute different stages of work across multiple locations, thereby increasing the robot's workload. However, it is essential to assess whether the investment in production reorganization justifies the effort and if it aligns with the principles of Industry 4.0.

An industrial robot is a programmable, automated machine designed to execute a range of tasks in manufacturing and industrial environments. These robots are equipped with various sensors, actuators, and end-effectors that allow them to manipulate objects, perform repetitive tasks, and carry out complex operations with precision and efficiency. Industrial robots are typically used to streamline production processes, increase productivity, and improve the overall quality of manufactured products.

These robots can be categorized into different types based on their configurations and applications, such as articulated robots, cartesian robots, delta robots, and collaborative robots (cobots). They are usually controlled through computer programs that guide their movements, and they can be integrated into existing production lines or workspaces to work alongside human operators in a collaborative or autonomous manner.

Industrial robots have been a transformative technology in manufacturing industries, providing various benefits such as reduced labour costs, improved safety by taking over hazardous tasks, enhanced product consistency, and increased production throughput. The adoption of industrial robots has been a crucial aspect of Industry 4.0, which emphasizes the integration of advanced automation, data exchange, and smart technologies in manufacturing processes. As technologies and capabilities of industrial robots continue to evolve, their role in transforming manufacturing industries is expected to grow further.

Simulation software plays a crucial role in making informed decisions regarding robotization. Simulating industrial solutions, including robots, has become more accessible and easier with the availability of various software tools in the market.

Industrial robot simulation software allows manufacturing companies, especially small and medium-sized enterprises (SMEs), to assess the feasibility and benefits of integrating robots into their production processes without making substantial investments upfront. These software tools create virtual models of the proposed robotic systems, enabling engineers and decision-makers to evaluate the robot's performance, efficiency, and potential challenges in a risk-free environment.

Through simulation, companies can test different robot configurations, programming sequences, and production layouts to identify the most optimal solution for their specific needs. This virtual testing helps in avoiding costly mistakes during the actual implementation of robots on the shop floor. Companies can also compare different robot models and technologies to select the one that best aligns with their requirements and budget constraints.

Moreover, industrial robot simulation software enables SMEs to overcome the limitations of available workload that might hinder the justification of robotization. By analyzing the production processes and distribution of work across multiple locations, simulations can identify potential bottlenecks, inefficiencies, or areas where robot deployment can significantly enhance productivity. By integrating robots strategically into the production flow, SMEs can maximize their benefits while minimizing disruptions to existing operations.

Furthermore, simulation software also plays a crucial role in the integration of mobile robots within the industrial landscape. The emergence of mobile robots has opened new possibilities for organizing internal logistics and enhancing the overall efficiency of production processes. However, companies, especially SMEs, often face the question of whether they can provide sufficient work for a mobile robot and if production needs to be reorganized accordingly.

Simulation provides a quick and effective way to address this question. By creating virtual representations of mobile robots and the proposed production environment, companies can test different scenarios and workflows. They can analyze how mobile robots navigate through the workspace, interact with other machinery, and perform material handling tasks.

Various technologies are employed in mobile robotics, with autonomous mobile robots (AMRs) gaining popularity due to their practicality and versatility in modern industrial settings. Simulation software allows companies to assess the capabilities of AMRs in specific manufacturing contexts. They can evaluate factors such as navigation algorithms, obstacle avoidance mechanisms, and battery life to ensure that the chosen AMR suits their operational requirements.

Moreover, some mobile robots are designed to work collaboratively with humans, operating without the need for physical guides attached to the ground. Instead, they utilize advanced technologies like LIDAR (Light Detection and Ranging) to navigate autonomously. Simulation software aids in evaluating the effectiveness of collaborative mobile robots and optimizing their cooperation with human operators.

Safety considerations also play a crucial role when deploying fast-moving mobile robots, especially in shared spaces with human workers. Simulation helps in identifying potential collision points and optimizing the paths of mobile robots to eliminate human-robot contact. By virtually testing safety measures, companies can ensure a safe coexistence of mobile robots and human workers in the same workspace.

By utilizing flexible industrial equipment, such as collaborative robots and mobile robots, SMEs have numerous opportunities to optimize their production processes. Combining these resources allows for a dynamic approach to resource allocation, where a collaborative robot can move between different workstations while a mobile robot handles delivery and retrieval tasks. This flexible strategy ensures that the collaborative robot is employed at workstations with sufficient workload to justify its utilization.

Utilizing flexible industrial equipment, such as collaborative robots and mobile robots, presents SMEs with numerous opportunities to optimize their production processes. By combining these resources, a collaborative robot can move between different workstations while a mobile robot handles delivery and retrieval tasks. This approach offers flexibility for SMEs, allowing the collaborative robot to be employed across multiple workstations where there is sufficient workload to justify its utilization. The automation of moving an industrial robot between these workstations can be achieved using a mobile robot. Consequently, this flexible resource allocation strategy minimizes the need for extensive production changes.

There is a clear need to develop approaches that enhance the operational efficiency of industrial robots, enabling their utilization for diverse tasks across multiple locations. This research aims to address the challenges faced by SMEs in adopting reconfigurable manufacturing solutions based on autonomously movable industrial robot arms. By examining the benefits and feasibility of integrating collaborative robots and mobile robots, this study seeks to provide insights and strategies for optimizing the utilization of industrial robots in SMEs.

Abbreviations

AI	Artificial Intelligence
AMS	Automated Manufacturing Systems
BMS	Battery Management System
CIRP	The International Academy for Production Engineering
CNC	Computer Numeric Control
cobot	Collaborative robot
CPS	Cyber-Physical Systems
CT	Cycle Time
DAAAM	Danube Adria Association for Automation and Manufacturing
DT	Digital Twin
ERP	Enterprise Resource Planning
GPS	Global Positioning System
HMI	Human Machine Interface
HRC	Human-Robot Collaboration
IFR	International Federation of Robotics
I4.0	Industry 4.0
IoT	Internet of Things
IMECC	Innovative Manufacturing Engineering Systems Competence Center
IMS	Intelligent Manufacturing System
INS	Inertial Navigation System
IR	Industrial Robot
LIDAR	Light Detection and Ranging
M2M	Machine to Machine
MES	Manufacturing Execution System
MSD	Manufacturing System Design
OEE	Overall Equipment Effectiveness
RFID	Radio Frequency Identification
R&D	Research and Development
ROI	Return on Investment
RQ	Research Question
SaaS	Software as a Service
SLAM	Simultaneous Localization and Mapping
SM	Smart Manufacturing
SME	Small and Medium-sized Enterprises
TTK UAS	TTK University of Applied Sciences
WIP	Work in Progress

1 Background

The thesis is founded upon original articles authored by the researcher. The integration of self-authored research articles enhances the credibility and scholarly value of the thesis, facilitating a comprehensive and knowledge-driven investigation into the chosen topic.

1.1 Research problem and questions

Robotization has been a hot topic among industrial companies for a long time, but unfortunately we don't see robots in most of the manufacturing companies yet (Kangru, Riives, Otto, Kuts, & Moor, 2020) (Mahmood, Otto, Golova, Kangru, & Kuts, 2020). Using an industrial robot requires also providing enough work to be fulfilled by the robot. Determination if robotization is suitable for the company is one of the most critical issues before selecting an industrial robot and starting to design the robot cell (Kangru, Riives, Mahmood, & Otto, 2019) (Kangru, Pohlak, Riives, Pohlak, & Mahmood, 2018). In the case of small and medium-sized companies (SME), this is one of the main obstacles why a robot is not bought, because there is not enough workload to offer in a single specific place. To increase the robot's workload, production could be reorganized in a way that several different stages of the work are made achievable to the robot (Vaher, Kangru, Otto, & Riives, 2019). This would increase the workload of the robot, but does this investment in production reorganization justify itself and is worth to try? The use of robotic and automated production systems also requires certain fundamental changes in the structure of production, so that new technologies can be implemented according to the principles of Industry 4.0 (Moor, Vaher, Riives, Kangru, & Otto, 2021). Various simulation software is of great help in making robotization decisions. Simulating industrial solutions, including robots, has become accessible and relatively easy these days, also there are many relevant software's available on the market (Vaher, Mahmood, Otto, & Riives, 2021) (Golova, Mahmood, Raamets, & ., 2021) (visualcomponents.com, 2022).

The rapid development of technology has also brought mobile robots to the industry, which help organize internal logistics. When using mobile robots, SMEs have the same question, whether it is possible to offer the robot enough work and whether production needs to be reorganized for this. This question can be answered with simulation. Different technologies are used in mobile robotics. Recent years have seen a dramatic rise in the popularity of autonomous mobile robots (AMRs) due to their practicality and potential uses in the modern world (Longanathan, 2023). With fast-moving machines, attention must be paid to safety, which may mean reconfiguring production so that human-robot contact is eliminated. There are also such mobile robots that work together with people and do not need to move according to a line, or some other guide physically attached to the ground. These kinds of robots use LIDAR technology (Markis, Papa, & Kaselautzke, 2019) (Falkowski, Smater, Koper, & Mysliwiec, 2020) (mir.com, 2022). The use of flexible industrial equipment, such as a collaboration robot and a mobile robot, gives the company many new opportunities to plan its production. With the use of flexible solutions, production does not necessarily have to be re-planned, but these solutions can be integrated into the existing system.

Particularly effective cooperation occurs when these two resources are put to work together, where the cooperation robot moves between different workstations and the mobile robot handles its delivery and retrieval (Vaher, Kangru, Otto, & Riives, 2019). Such an association would be a flexible way for an SME to use a collaborative robot in a situation where there is not enough work for the robot in one specific workplace, but there are several workplaces in addition to the entire production where the robot would have enough work to justify its use. Moving an industrial robot between these jobs can be automated with a mobile robot (Vaher, Kangru, Otto, & Riives, 2019). This way of using resources gives a very flexible approach without having to make big changes in production.

Research problem: There is a need to develop approaches to enhance the operational efficiency of industrial robots, enabling their utilization for diverse tasks across multiple locations.

The following research questions (RQ) are thus considered:

RQ1: How can small and medium-sized enterprises (SMEs) be enabled to utilize robots more effectively in situations where there is not enough workload to justify the installation of a robot at a single location?

RQ2: What combination of technologies can be used to enable industrial robots to operate autonomously and achieve sufficient precision for servicing industrial equipment (e.g., latches, CNC machines, etc.) while also being mobile?

RQ3: How to evaluate the need of a flexible robot solution or robots in quantity based on the information of production batch and parts per batch?

The research questions are answered stepwise in the following articles.

Article I, II and V have answered RQ1, giving an overview how a robot arm can be used and transported on shop floor and which technologies we combine to achieve a fully functioning system.

Article III has answered RQ2, solving the positioning inaccuracy of mobile robots to achieve the same accuracy of a robot arm.

Article IV has answered RQ3, explained the use of a simulation tools and analysed some use cases to show the simplicity of modern simulation tools.

1.2 New developments and trends

Over the last ten years, there has been a significant shift in people's attitudes towards robots. In the past, robots were primarily associated with science fiction and were often viewed as a threat to human jobs. However, with the rise of automation and the increasing use of robots in various industries, people's attitudes towards robots have changed.

Nowadays, there is a growing acceptance of robots as a useful tool in improving productivity, safety, and efficiency in many different industries. Robots are no longer viewed as a threat to human jobs but rather as a complement to human skills and abilities. Many people recognize the potential of robots to perform repetitive, dangerous, and unpleasant tasks that are difficult or impossible for humans to perform.

Recent studies have shown that many people have a positive attitude towards robots and are willing to work alongside them. These changing attitudes towards robots have led to an increase in their use across a range of industries, including manufacturing, healthcare, and logistics. As the technology continues to advance and robots become more sophisticated and capable, it is likely that people's attitudes towards them will continue to evolve. New trends in the field research of the robotics are rising, such as the development of soft robots, cooperative robots, and human-robot interaction. (Latikka, Savela, Koivula, & Oksanen, 2021) found that people had a more positive attitude towards robots as equipment than as coworkers, and preferred non-autonomous robots over fully autonomous ones in the work-life context. (Warta, 2015) developed a Robot Perception Scale to measure attitudes towards robots, which can be used to further understand human-robot interactions. (Nomura, Kanda, Suzuki, Yamada, & Kato, 2009) discussed the importance of concerns about emotional interaction in the social acceptability of robots. (Savela, Turja, & Oksanen, 2018) found that attitudes towards robots were generally positive in various occupational fields, with telepresence robots being highly approved in healthcare settings.

The field of industrial robotization is constantly evolving, with new developments and trends emerging regularly. Some of the recent developments and trends in the field include:

1. **Collaborative robots**: Collaborative robots, also known as cobots, are robots that can work alongside human workers. These robots are designed to be safe, flexible, and easy to use, and can perform a variety of tasks, from assembly to inspection. The market for cobots is growing and is expected to continue to expand in the coming years.
2. **Artificial intelligence**: Artificial intelligence (AI) is becoming increasingly important in the field of industrial robotics. AI algorithms can be used to optimize robot performance, automate decision-making processes, and improve overall efficiency. As AI technology continues to advance, it is expected to have a significant impact on the field of industrial robotics.
3. **Advanced sensing and perception**: Sensing and perception technologies are critical for enabling robots to interact with their environment. Recent developments in sensing and perception technology, such as 3D vision and haptic feedback, are allowing robots to perform tasks more accurately and efficiently.
4. **Cloud robotics**: Cloud robotics is an emerging trend in which robots are connected to cloud-based services, allowing them to access and process large amounts of data. This enables robots to learn from their experiences and make better decisions, leading to improved performance and productivity.
5. **Mobile robots**: Mobile robots, which can move autonomously around a factory or warehouse, are becoming increasingly popular. These robots can be used for tasks such as material handling, inspection, and inventory management, and are often equipped with advanced sensing and perception capabilities.

6. **Modular robotics**: Modular robotics refers to the use of modular components to create robots that can be easily customized and adapted to different tasks. This approach allows companies to quickly and efficiently develop robots that meet their specific needs, without having to start from scratch each time.
7. **Industry 4.0**: Industry 4.0 is a term used to describe the integration of advanced technologies, such as Internet of things (IoT), AI, and cloud computing, into the manufacturing process. This trend is expected to have a significant impact on the field of industrial robotics, as it will enable robots to be more connected and data driven.
8. **Industry 5.0**: Industry 5.0 is the next phase of industrial development that emphasizes the collaboration between humans and advanced technologies for enhanced productivity and customization in manufacturing. It leverages human creativity and problem-solving skills while integrating robotics, AI, and IoT systems to create a harmonious work environment.

A more detailed discussion of the technological framework's methodology is presented in Chapter 2.

1.3 Objectives

The objective of this study is to investigate the underlying causes of the limited adoption of industrial robots within small and medium-sized enterprises (SMEs), and to devise a novel approach for enhancing the efficient utilization of industrial robots in this sector.

The main objectives of the thesis are:

Objective 1: To develop approaches that enable small and medium-sized enterprises (SMEs) to effectively utilize robots in situations where there is insufficient workload at a single location.
Objective 2: To identify and evaluate the combination of technologies that enable industrial robots to operate autonomously and achieve sufficient precision for servicing industrial equipment while also being mobile.
Objective 3: To assess the need for flexible robot solutions or multiple robots based on production batch information and parts per batch, providing guidance on optimizing the utilization of resources.
Objective 4: To explore the use of simulation tools to evaluate and analyze different scenarios, demonstrating the effectiveness of modern simulation tools in decision-making related to robotization and production reorganization.
Objective 5: To provide insights and findings through a series of articles that address the research questions and contribute to the understanding and advancement of operational efficiency in utilizing industrial robots in various manufacturing setting.

By addressing these objectives, the research aims to provide practical solutions and valuable insights for SMEs considering robotization, production reorganization, and the implementation of collaborative and mobile robotics systems.

The outcome of this research endeavour will be the formulation of a solution to facilitate the more widespread adoption of industrial robots within the SME context. The proposed solution aims to overcome a primary barrier to robot deployment, namely, the lack of sufficient workload to justify the installation of a robot at a single location without necessitating the relocation of the entire production process.

1.4 Research process and structure of the dissertation

Several methods and techniques were utilized in various stages of the research process. Initially, pilot data was gathered from production company management and researchers and analyzed. Subsequently, information was obtained through a literature review, and the research area, objectives, and questions were developed. A comprehensive literature review was then conducted to gather additional information and identify a research gap. Based on the collected data, an analysis was conducted, and conclusions were drawn. To propose potential solutions, the case study methodology was employed, and these solutions were verified through experiments conducted in university laboratories or simulations conducted using various commercial software. The final conclusions were drawn based on the results obtained, and recommendations for future research, as well as research limitations, were also proposed.

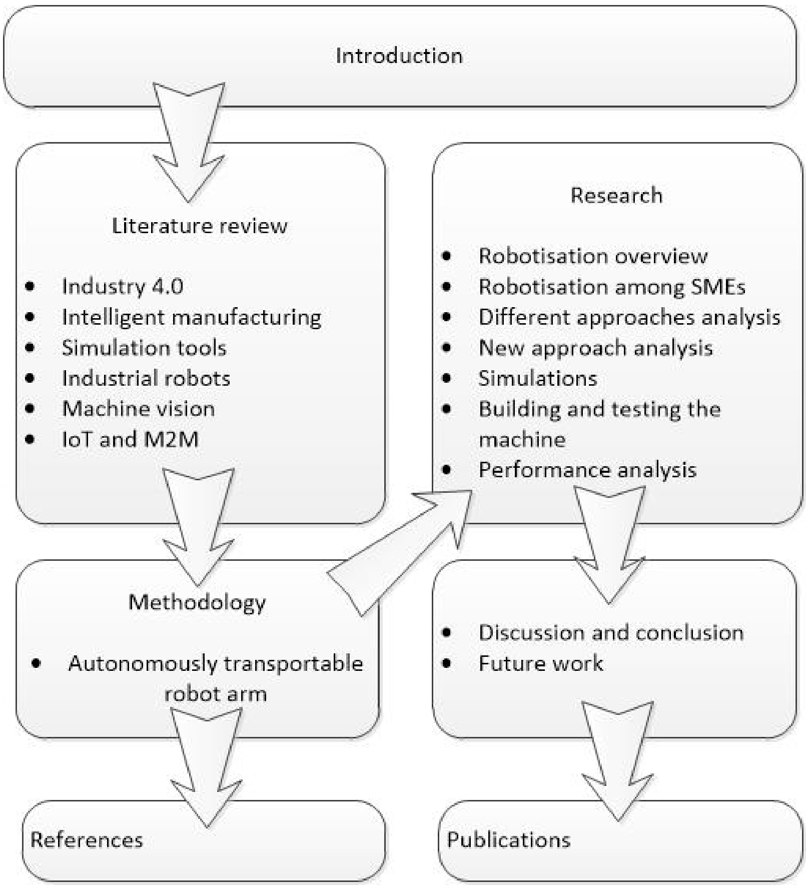


Figure 1. Structure of the dissertation.

2 Literature review

The literature review section comprises of explanation of the concepts, methods, and definitions required for composing the thesis. Additionally, this chapter will establish the essential technological framework in which the proposed solution of this thesis should align.

2.1 Industry 4.0

Industry 4.0 is a term used to describe the fourth industrial revolution that is currently underway. It represents a new era of manufacturing and production, characterized by the integration of digital technologies, such as the Internet of Things (IoT), artificial intelligence (AI), robotics, big data analytics, etc. into the manufacturing processes. Industry 4.0 aims to create a smart, interconnected factory that can sense, analyze, and optimize production processes in real-time. This is achieved by cyber-physical systems (CPS), which are composed of physical components such as sensors, machines, robots, and digital components such as data analytics and cloud computing. (Shyamsunder, 2023) explores the origins, key technologies, transformative impact, and future perspectives of Industry 4.0. (Helmold, 2019) discusses the role of artificial intelligence (AI) within Industry 4.0, highlighting its contribution to creating smart factories. (Santos, Alberto, Lima, & Charrua-Santos, 2018) emphasizes the challenges and opportunities presented by Industry 4.0, including the use of cyber-physical systems, the Internet of Things, and cloud computing. Overall, these papers provide insights into the various aspects and implications of Industry 4.0 in manufacturing and beyond.

The main goal of Industry 4.0 is to improve manufacturing efficiency, productivity, and flexibility, while reducing costs and waste. This is achieved through the integration of data and the use of intelligent systems to optimize production processes. For example, by using sensors and data analytics, manufacturers can monitor the performance of machines and identify opportunities for optimization, such as reducing downtime or improving product quality. Industry 4.0 has the potential to transform traditional production systems into more efficient, flexible, and responsive operations. These papers collectively support the idea that Industry 4.0 aims to improve manufacturing efficiency, productivity, and flexibility while reducing costs and waste through the integration of data and the use of intelligent systems. (Harda, Tóth, & Illés, 2020) highlights the potential of Industry 4.0 to increase system flexibility and optimize production. (Brecher, Müller, Dassen, & Storms, 2021) emphasizes the importance of automation technology in achieving the goals of Industry 4.0 and enabling smart manufacturing. (Jeyalakshmi, Sowmitha, & Dheekshana, 2019) discusses how Industry 4.0 enables enterprises to integrate their employees, machines, processes, and products into a single network for data collection, analysis, and performance improvement.

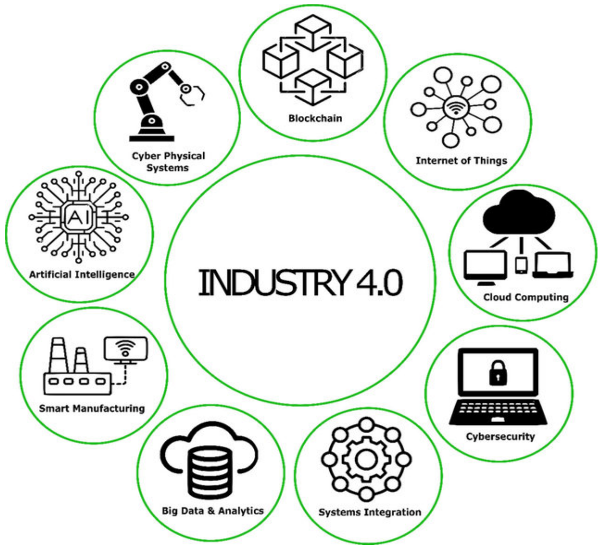


Figure 2. Main pillars of Industry 4.0 (Mendes, Bortoli, & Costa, 2020)

Industry 4.0 has a significant impact on existing production systems. Some of the effects are:

- Increased efficiency: Industry 4.0 technologies enable real-time monitoring, data analysis, and optimization of production processes, leading to increased efficiency and productivity.
- Cost savings: The use of automation, machine learning, and predictive analytics in Industry 4.0 can help identify cost-saving opportunities and optimize the use of resources.
- Customization: Industry 4.0 technologies enable mass customization by allowing for the efficient production of small batches with minimal downtime.
- Safety: Collaborative robots and other Industry 4.0 technologies can help improve workplace safety by taking over dangerous and repetitive tasks, reducing the risk of accidents.
- Skilled workforce: Industry 4.0 technologies require specialized knowledge and skills, leading to an increased demand for highly skilled workers.
- Data security: The use of connected devices in Industry 4.0 increases the risk of cyber-attacks, making data security a critical concern.

In addition, Industry 4.0 also involves the use of new business models, such as mass customization and servitization, which allow manufacturers to better respond to customer demands and provide value-added services. Servitization refers to the transformation of a product-centric business model into a service-oriented one (SaaS). This shift requires the adoption of new business models such as mass customization and the integration of digital technologies. (Silva, Viagi, & Giacaglia, 2018) highlights the relationship between servitization and digitalization, identifying them as sources of competitive advantage. Industry 4.0 represents a significant shift in the way that manufacturing is conducted, with a focus on digitalization, automation, and interconnectivity. It has the potential to revolutionize manufacturing processes and create new opportunities for innovation, growth, and sustainability. However, it also presents challenges related to data privacy and security, workforce skills, and the need for collaboration across industries and stakeholders (Mendes, Bortoli, & Costa, 2020). (Shyamsunder, 2023) emphasizes the transformative impact of Industry 4.0 on various sectors and the need for collaboration and effective strategies for successful implementation. (Umachandran, Jurčić, Corte, & Ferdinand-James, 2019) discusses how Industry 4.0 is changing management systems and competencies, requiring a skilled workforce with cross-functional capacities. (Santos, Alberto, Lima, & Charrua-Santos, 2018) describes Industry 4.0 as a paradigm shift that enables communication along the value chain through technologies like cyber-physical systems, the Internet of Things, and cloud computing. (Subhadra, 2021) highlights the integration of digitalization with conventional manufacturing processes and the technologies involved, such as artificial intelligence, big data, and the industrial internet of things. Overall, the papers suggest that Industry 4.0 has the potential to revolutionize manufacturing processes and create new opportunities for innovation, growth, and sustainability.

The use of robots is a key element of Industry 4.0, as it enables the automation and optimization of manufacturing processes. Robots can perform a wide range of tasks, from simple material handling and assembly operations to more complex tasks such as inspection, quality control, and even decision-making. (Javaid M. , Haleem, Singh, & Suman, 2021) emphasizes that robotics is a key technology in Industry 4.0, enabling automation, precision, and cost-effectiveness in manufacturing processes. (Contreras J. , 2019) proposes a procedure for integrating industrial robots into Industry 4.0 systems, enhancing interoperability, and offering new value opportunities through data analysis. (Bayram & Ince, 2018) discusses how advances in information technology, such as artificial intelligence and big data, are transforming the use and design of robots in the industry, making them more intelligent and capable of smarter decision-making. Overall, these papers highlight that robots play a crucial role in automating and optimizing manufacturing processes in the context of Industry 4.0.

In Industry 4.0, robots are integrated with other digital technologies, such as sensors, data analytics, and machine learning algorithms, to create intelligent systems that can monitor and optimize production processes in real-time. For example, robots can be equipped with sensors that can detect defects or anomalies in the manufacturing process, and then use machine learning algorithms to adjust their operations to optimize production quality and efficiency. (Karabegović, 2020) emphasizes the application of robots, IoT, and smart sensors in the metal industry to increase productivity and improve product quality. (Javaid M. , Haleem, Singh, & Suman, 2021) emphasizes the extensive capabilities of robotics in manufacturing, including automation, data collection, complex tasks, and artificial intelligence. (Bayram & Ince, 2018) discusses the advances in information technology, such as artificial intelligence and big data, that are shaping the design and utilization of robots in Industry 4.0. Overall, these papers demonstrate how robots integrated with digital technologies play a crucial role in monitoring and optimizing production processes in real-time.

Human-robot collaboration (HRC) within the context of Industry 4.0 refers to the integration of advanced robotics and automation technologies with human workers in industrial environments. The aim of HRC is to create more efficient, flexible, and safe production systems by combining the strengths of humans and robots. HRC can take various forms, such as cooperative, collaborative, and cognitive HRC, and requires the use of advanced technologies, such as sensors, machine learning, and natural language processing. (Semeraro, Griffiths, & Cangelosi, 2021) provides a systematic review of recent research on HRC and machine learning. It analyzes various collaborative tasks, evaluation metrics, and cognitive variables modeled in HRC. The paper emphasizes the importance of incorporating time dependencies in machine learning algorithms for HRC.

The use of robots in Industry 4.0 also enables greater flexibility and customization in manufacturing. The use of robots is an essential component of Industry 4.0, as it enables manufacturers to achieve greater efficiency, productivity, and flexibility in their operations. By integrating robots with other digital technologies, manufacturers can create intelligent systems that can optimize production processes and enable new levels of automation and customization.

2.2 The future of industrial robotization

The future of industrial robotization is expected to be driven by advancements in robotics technology, artificial intelligence, and the IoT. Integration of these technologies can lead to new applications for robotics, such as in autonomous vehicles and service robotics. The need for continued innovation and collaboration between academia and industry is needed to realize the full potential of industrial robotization. (Kodaira, 2016) emphasizes the need for innovation in system integration, materials, and elemental technologies to expand the usage of industrial robots. (Tantawi, Sokolov, & Tantawi, 2019) highlights the shift from Industry 3.0 automation to Industry 4.0 collaboration, where AI enables collaborative tasks and China leads the industrial robotics market. (Bayram & Ince, 2018) discusses how Industry 4.0 revolution and advancements in AI, cloud, and Big Data are changing the use and design of robots in the industry.

With the development of collaborative robots, or cobots, the use of robots in manufacturing is becoming more widespread, as they can work alongside human workers, increasing efficiency and productivity. In the future, cobots are expected to become more intelligent and adaptable, with advanced sensing and learning capabilities, allowing them to perform a wider range of tasks. (Kakade, Patle, & Umbarkar, 2023) emphasizes the adaptability and flexibility of cobots in carrying out complex tasks, making them a significant asset in manufacturing. (Vojić, 2020) discusses how cobots are being used alongside human workers for tasks like quality inspection and pick-and-place, highlighting their affordability and ease of use. (Borboni, Vishnu, Reddy, & Elamvazuthi, 2023) focuses on the expanding role of artificial intelligence in cobots, highlighting their ability to enhance employee performance and improve working conditions. (Silva, Regnier, & Makarov, 2023) addresses the challenges in evaluating intelligent cobots and emphasizes the need for methods and resources to foster their development and acceptability.

Another key trend in the future of industrial robotization is the integration of robotics with other technologies, such as AI and IoT, to create more advanced and automated production systems. This will lead to a more interconnected and data-driven manufacturing environment, with robots being used to monitor and analyse production processes and adjust operations in real-time. (Zenta & Gerald, 2020) emphasizes the importance of holistic integration in Industry 4.0, considering products, production processes, and business activities. (Tsigie & Dagnaw, 2021) highlights how robotic systems and IoT can proactively monitor and adapt to changes in production lines, leading to improved reliability, production, and customer satisfaction.

Overall, the future of industrial robotization is expected to bring about significant changes to the manufacturing industry, including increased efficiency, flexibility, and customization capabilities. As the technology continues to advance and become more accessible, it is likely that more companies, including SMEs, will adopt robotic systems to stay competitive in an increasingly automated marketplace.

Industry 5.0 topics are already being discussed (seminars, articles). Industry 5.0 is a concept that builds upon the principles of Industry 4.0, with a focus on bringing the human element back into the manufacturing process. Unlike Industry 4.0, which focuses on automation and digitization, Industry 5.0 emphasizes the importance of human workers collaborating with robots and advanced technologies to create more efficient and sustainable manufacturing processes. (Raffik & Ramamoorthy, 2023) highlights the use of collaborative robots (cobots) in Industry 5.0 to increase productivity and safety in various industrial sectors. (Alves, Lima, & Gaspar, 2023) examines whether Industry 5.0 is truly human-centered and emphasizes the importance of empowering human operators to improve their skills and competences in collaboration with digital technologies. (Iqba, Carman, & Ren, 2022) discusses how Industry 5.0 extends the development of Industry 4.0 by considering the contribution of humans to the manufacturing process and the idea of sustainable development goals. (Tiwari, Bahuguna, & Walker, 2022) emphasizes the concept of human-robot co-working in Industry 5.0 and how it overcomes the limitations of previous industrial revolutions.

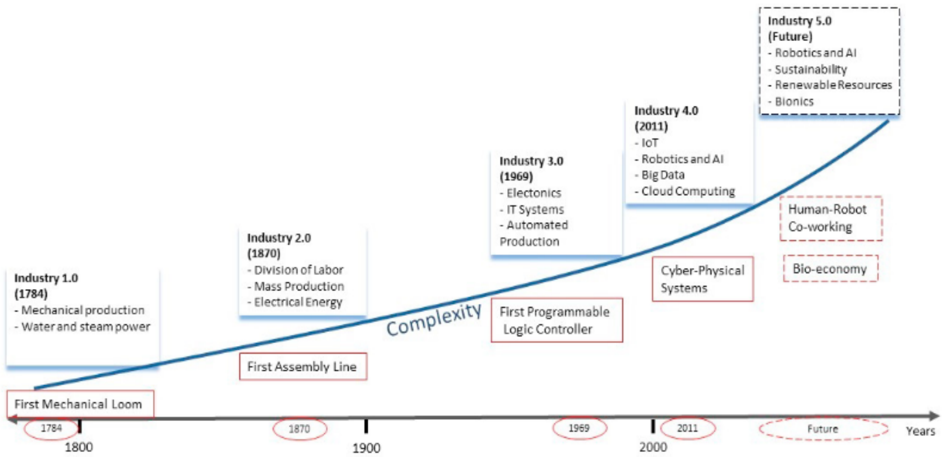


Figure 3. From Industry 1.0 to Industry 5.0 (Demira, Dövena, & Sezenb, 2019)

In Industry 5.0, robots are designed to work alongside human workers, taking on the most dangerous, repetitive, and physically demanding tasks while leaving the complex and creative work to humans. This approach is seen to create meaningful and fulfilling work for human workers, while also improving productivity and efficiency (Demira, Dövena, & Sezenb, 2019).

While Industry 5.0 is still a relatively new concept, some experts believe that it will become increasingly important in the coming years as companies look for ways to balance the benefits of automation with the need for human workers in the manufacturing process. It's important to note that Industry 5.0 is not a replacement for Industry 4.0, but rather an evolution of it. Both concepts will continue to play important roles in shaping the future of manufacturing, with Industry 5.0 emphasizing the importance of human-robot collaboration and Industry 4.0 focusing on automation and digitization.

2.3 Intelligent manufacturing

Intelligent manufacturing refers to the use of advanced technologies such as the IoT, AI, robotics, and data analytics to create highly automated, adaptive, and responsive production systems. This approach emphasizes the integration of various manufacturing processes and systems into a coherent and highly efficient whole, enabling manufacturers to achieve higher levels of productivity, quality, and flexibility.

One key aspect of intelligent manufacturing is the use of data and analytics to improve process control and decision-making. By collecting and analysing data from various sensors and other sources, manufacturers can gain a better understanding of their processes and identify areas for improvement. This can lead to more efficient and effective production, as well as reduced waste, downtime, and costs. (Iftikhar, Baattrup-Andersen, Nordbjerg, Bobolea, & Radu, 2019) emphasizes the value of data and proposes data analytic techniques to analyze manufacturing data, aiming to improve operational efficiency and achieve competitive benefits. (Shang & You, 2019) discusses the role of data analytics and machine learning in monitoring, control, and optimization of industrial processes, with a focus on interpretability and functionality of machine learning models. (Wang, Xu, Zhang, & Zhong, 2021) reviews big data analytics (BDA) for intelligent manufacturing systems, discussing the concept of big data, methodologies, key technologies, and applications, highlighting BDA as a core technology for empowering intelligent manufacturing.

Another important aspect of intelligent manufacturing is the use of advanced robotics and automation technologies. These technologies enable manufacturers to automate many routine and repetitive tasks, freeing up human workers to focus on more complex and value-added activities. Intelligent manufacturing also involves the use of cobots, which can work alongside human workers to perform tasks that require a high degree of dexterity or judgment. (Galin, Meshcheryako, Kamesheva, & Samoshina, 2020) emphasizes the benefits of implementing cobots in intelligent manufacturing, which can optimize production processes and improve efficiency. (Wierzbowski, 2019) discusses how cobotization and robotization of technological lines and transport systems lead to advanced automation of logistics processes in smart factories.

Intelligent manufacturing also includes the use of advanced processes, such as digital manufacturing. These technologies can enable manufacturers to produce highly complex and customized products more efficiently and cost-effectively than traditional manufacturing methods. Digital manufacturing refers to the use of digital technologies and advanced systems to optimize and improve various aspects of the manufacturing process. It involves the integration of digital tools, data analytics, automation, and connectivity to enhance productivity, efficiency, and flexibility in manufacturing operations. (Zhong, Xu, Klotz, & Newman, 2017) provides a comprehensive review of intelligent manufacturing in the context of Industry 4.0, highlighting key technologies such as the Internet of Things (IoT), cloud computing, and big data analytics. In digital manufacturing, traditional manufacturing processes are digitized, allowing for better control, monitoring, and analysis of production systems.

The goal of intelligent manufacturing is to create highly agile, responsive, and efficient production systems that can adapt quickly to changing market demands and customer needs. By leveraging advanced technologies and data analytics, manufacturers can achieve new levels of productivity, quality, and flexibility, while also reducing costs and improving sustainability. (Davis, et al., 2015) emphasizes the shift from vertically optimized manufacturing enterprises to responsive value chains that focus on agility, productivity, energy efficiency, and environmental sustainability. (Ghahramani, Qiao, & Zhou, 2020) discusses the use of artificial intelligence and machine learning to optimize manufacturing processes and enable intelligent automation. (Davis, Edgar, Porter, & John Bernaden, 2012) highlights the transformative impact of smart manufacturing on demand-dynamic economics, real-time performance management, and workforce involvement. (Mekid, Pruschek, & Hernandez, 2009) explores the challenges and objectives of intelligent reconfigurable manufacturing systems, including zero-defect workpieces and just-in-time production.

Intelligent production and industrial robots are closely related. Industrial robots are one of the key components of intelligent production (Preuveneers & Ilie-Zudor, 2017) (Porter, Bernaden, & Sarli, 2012). They provide the flexibility and precision required for a range of manufacturing processes, including assembly, welding, painting, and material handling. Industrial robots are a key enabler of intelligent production, providing the flexibility and precision required to implement advanced manufacturing techniques.

The use of industrial robots in intelligent production has several advantages, including improved quality, increased efficiency, and reduced costs. For example, robots can perform repetitive tasks more consistently and accurately than humans, leading to improved product quality. They can also work around the clock, increasing production output and reducing manufacturing lead times. (Yunze, 2022) highlights the wide application of industrial robots in intelligent manufacturing, leading to improved economic development and industrial structure. (Galin, Meshcheryako, Kamesheva, & Samoshina, 2020) emphasizes the benefits of collaborative robots (cobots) in intelligent manufacturing, including increased automation, improved efficiency, and enhanced human-robot interaction. (Perzylo A. , Rickert, Kahl, & Somani, 2019) discusses the need for smart robots in flexible manufacturing to meet the demands of rapidly changing products and achieve seamless human-robot collaboration.

In addition, robots can be integrated with other intelligent production technologies such as sensors and data analytics, enabling real-time monitoring and optimization of manufacturing processes. This can help to identify inefficiencies and opportunities for improvement, leading to further productivity gains and cost reductions.

Overall, the integration of industrial robots into intelligent production systems is expected to play a key role in the development of advanced manufacturing processes and the creation of more efficient and sustainable factories.

2.4 Simulation tools

Simulation tools are an essential component of intelligent manufacturing. They are used to model and simulate various aspects of the manufacturing process, including production planning, material flow, machine utilization, and product design. By creating a virtual environment to test and optimize production processes, simulation tools can improve efficiency, reduce costs, and increase product quality. (Williams, 2002) emphasizes the benefits of simulation in reducing costs, increasing production quotas, and improving performance metrics. (Hosseinpour & Hajihosseini, 2009) highlights the importance of simulation as a valuable work tool in manufacturing, providing low-cost and fast analysis. (O'Kane, Spenceley, & Taylor, 2000) discusses how simulation can provide valuable insights into the operational characteristics of manufacturing systems, allowing for experimentation with different scenarios and identifying the best course of action. (Zhang, Zhou, Ren, & Laili, 2019) reviews the application of modeling and simulation technology in manufacturing, highlighting its role in all stages of the product life cycle.

Simulation tools can be used to create digital twins of the manufacturing process. A "digital twin" refers to an exact digital replica of a manufacturing process, created using simulation tools, which allows for the testing of various scenarios and optimization of production before implementing physical changes to the actual production line. (Somme, Josip, Stobrawa, & Soden, 2020) proposes a novel approach to automatically generate a digital twin using fast scans and object recognition. (Azangoo, Taherkordi, & Blech, 2020) discusses the use of Unified Modeling Language (UML) to model digital twins in complex manufacturing systems, allowing for simulation, verification, and optimization. (Vachálek, Bartalský, Rovný, Šišmišová, & Morháč, 2017) presents a digital twin concept for continuous optimization of production processes and proactive maintenance. (Ali, Patel, Breslin, Harik, & Sheth, 2021) highlights the potential of digital twins in smart manufacturing, including status monitoring, simulation, and visualization.

These digital twins can be used to simulate different scenarios, test changes, and optimize the production process before making any physical changes to the actual production line. This can help reduce the risk of costly mistakes and improve the efficiency of the manufacturing process. (Tao, Qi, Wang, & A., 2019) emphasizes that physical product data, virtual product data, and connected data are needed to support product design, manufacturing, and service phases. (Bao, Guo, Li, & Zhang, 2018) proposes a modelling and operations approach for digital twins in manufacturing, demonstrating improved production efficiency. (Nikolakis, Alexopoulos, Xanthakis, & Chryssolouris, 2018) focuses on linking virtual representations of human-based production tasks to their physical counterparts, enabling optimization through simulation-based approaches. (Rojek, Mikołajewski, & Dostatni, 2020) highlights the benefits of digital twins in sustainable production and maintenance, including the use of simulation models to improve tasks and processes. (Židek, Pitel, Adamek, Lazorík, & Hošovský, 2020) presents a case study of a digital twin for an experimental assembly system, showcasing real-time visualization and online optimization capabilities. These papers collectively emphasize the potential of digital twins to reduce risks, improve efficiency.

Simulation tools are also used for predictive maintenance, which involves using data from sensors and other sources to predict when a machine or component is likely to fail. By identifying potential problems before they occur, predictive maintenance can reduce downtime, improve machine reliability, and extend the life of equipment. (Szczerbicki & White, 1998) describes the implementation of computer simulation as a modeling and decision support tool for managing a condition-monitoring service group. (Contreras, Modi, & Pennathur, 2003) presents a case study where a simulation model integrated with equipment condition diagnostics was used to reduce production downtime and work in process inventory.

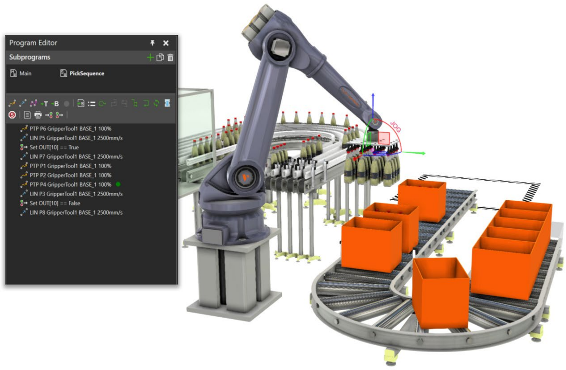


Figure 4. Process simulation (visualcomponents.com, 2022)

Industrial robots can be integrated into simulation tools for intelligent manufacturing to create virtual environments for testing and optimizing robotic systems. By incorporating real-world data into these simulations, manufacturers can evaluate different production scenarios and improve overall efficiency, safety, and quality of their manufacturing processes. Simulation tools can also help identify potential problems and risks before implementing a robotic system on the factory floor, reducing downtime and costs associated with system failure. (Zhang & Dershan, 2022) presents a simulation platform that incorporates the dynamics of robots into the control logic of industrial tasks, achieving high simulation fidelity. (Ou, Sung, & Hsiao, 2003) discusses the use of Virtual Reality Modeling Language (VRML) for visualization integration in manufacturing simulation systems, highlighting the benefits of high-fidelity visualizations for design and manufacturing tasks. (Wang, Fu, Hu, & He, 2021) develops a simulation platform for CNC intelligent manufacturing, demonstrating the combination of virtual simulation and practical verification to optimize teaching resources and improve learning outcomes. (Golnazarian & Hall, 2002) focuses on the application of industrial robots in manufacturing settings and emphasizes their contribution to enhancing flexibility in automation.

Simulations can be used to train operators on how to use industrial robots safely and effectively, improving workforce productivity and reducing the learning curve associated with new technology. Therefore, simulation tools are an integral part of the design, optimization, and implementation of industrial robots in intelligent manufacturing (Sekala, Kost, Banaś, Gwiazda, & Grabowik, 2022).

There are several simulation tools available to design a robot solution for a factory. Some of them include:

- **RobotStudio**: A software tool developed by ABB for the design and programming of industrial robots. It includes a 3D simulation environment to test and optimize robot programs before deployment.
- **Visual Components**: A 3D simulation software for factory automation that allows for the design and validation of robot cells, material handling systems, and other factory processes.
- **RoboDK**: A simulation and offline programming tool for industrial robots that allows for the creation, simulation, and validation of robot programs.

- **Siemens Tecnomatix**: A simulation software suite that includes tools for robot programming, simulation, and optimization.
- **Process Simulate**: A simulation software tool developed by Dassault Systèmes for factory automation that includes a 3D environment for robot programming and simulation.
- **Emulate3D**: A simulation software tool used for virtual commissioning, simulation, and testing of automation systems, including robotic solutions.

These simulation tools enable engineers and designers to create and test robot solutions in a virtual environment before deploying these in a factory setting. This reduces the risks and costs associated with deploying new robotic systems and enables faster and more efficient implementation of robot-based solutions.

2.5 Industrial robots

Definition of the term "industrial robot" is based on the definition of the International Organization for Standardization: an "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment" (ISO 8373:2021).

Industrial robots are automated machines designed to carry out repetitive and often dangerous tasks in a factory or production environment. They are typically used for applications such as assembly, material handling, painting, welding, and inspection. Industrial robots have become increasingly important in manufacturing due to their ability to improve productivity, quality, and safety, while reducing costs.

Industrial robots are composed of several key components, including the robot arm, controller, end-effector, and sensors. The robot arm consists of several joints, which allow the robot to move in multiple directions and perform tasks with high precision. The controller is the brain of the robot, which processes information from sensors and sends commands to the robot arm to perform specific tasks. The end-effector is the tool or attachment that the robot uses to interact with the work piece, such as a gripper or welding torch. Sensors are used to detect and measure various parameters, such as position, force, and temperature.

Industrial robots have several advantages over human labour, including increased productivity, quality, and safety. They can work continuously without getting tired or making mistakes, and they can operate in hazardous environments without putting human workers at risk. Industrial robots can also be programmed to perform complex tasks that are difficult or impossible for humans to do, such as welding or painting.

Despite the advantages of industrial robots, there are also some challenges associated with their use. Industrial robots require specialized programming and maintenance, which can be costly and time-consuming. They also require a significant initial investment, which may not be feasible for smaller companies. In addition, the use of industrial robots can lead to job displacement for human workers, which can have social and economic implications. (Karim & Verl, 2013) focuses on the challenges and obstacles in robot-machining, including the need to overcome the perception of robots as solely handling devices. (Bader & Rahimifard, 2018) explores the slow uptake of industrial robots in the food manufacturing industry, despite their potential benefits in improving flexibility and reconfigurability of production facilities.

Overall, industrial robots have become an important tool for manufacturers seeking to improve productivity, quality, and safety in their operations. As technology continues to evolve, the capabilities and applications of industrial robots are expected to expand, making them even more integral to the manufacturing process. (Clint, 2010) explores the potential future applications of industrial robots, particularly in challenging environments like the oil and gas industry, while also addressing the importance of human-robot interaction and finding the right balance of autonomy and engagement for effective operation.

Industrial robots can be classified based on various criteria, including their mechanical structure (articulated, cartesian, SCARA, delta, cylindrical, polar), application (welding, assembly, material handling, painting, pick-and-place, etc.), control system (hard automation, programmable, autonomous, collaborative), payload capacity, degree of freedom (DOF) and more.

Industrial robots can be broadly classified into seven main types based on their mechanical configuration and application, namely:

- **Articulated robots (a):** These are the most used type of industrial robots, consisting of multiple rotary joints connected by links that allow the robot to move in a wide range of motion. They are used for applications such as material handling, welding, painting, and assembly.
- **SCARA robots (b):** SCARA stands for Selective Compliance Assembly Robot Arm. These robots have three or four axes and are commonly used for assembly, packaging, and material handling applications.
- **Cartesian robots (c):** Also known as gantry robots, these robots have three linear axes and are used for applications such as pick-and-place, assembly, and packaging.
- **Delta robots (d):** Delta robots are used for high-speed pick-and-place applications, such as in the food and beverage industry. They have a parallel linkage design and are capable of very fast and precise movements.
- **Cylindrical Robots (e):** Cylindrical robots have a rotary joint at the base, like a polar coordinate system, allowing for both rotational and vertical movements. They are often used in applications like material handling and assembly, where a combination of horizontal and vertical motion is required.
- **Polar Robots (f):** Polar robots have a fixed base and a single rotary joint at the base, like a polar coordinate system. They are well-suited for applications that require precise positioning and rotation, such as screwdriving and painting.
- **Collaborative robots (Cobots) (g):** These robots are designed to work alongside humans and have built-in safety features that allow them to operate safely in a shared workspace. They are typically smaller and lighter than traditional industrial robots and can be easily reprogrammed for different applications.

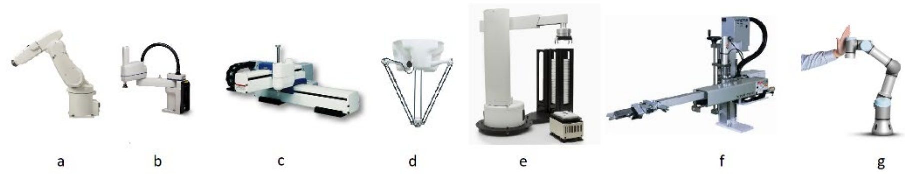


Figure 5. Examples of industrial robots based on their mechanical configuration - Articulated robots (a), SCARA robots (b), Cartesian robots (c), Delta robots (d), Cylindrical Robots (e), Polar Robots (f), Collaborative robots (Cobots) (g).

2.5.1 Articulated robots

Articulated robots are a type of industrial robot that are designed with rotary joints, allowing them to move in a wide range of motion. These robots typically have three or more axes, with each arm consisting of a series of linked segments that can be rotated or pivoted to achieve a desired motion. Articulated robots are commonly used in a variety of industrial applications, such as welding, painting, assembly, and material handling.

Articulated robots are known for their flexibility and precision, as they can be programmed to perform complex tasks with high accuracy. They are also able to operate in tight spaces, making them ideal for use in manufacturing environments where space is limited. In addition, articulated robots can be equipped with a variety of end effectors, such as grippers, welding torch, or spray guns, allowing them to perform a wide range of tasks.

Articulated robots are a valuable tool for improving efficiency and productivity in manufacturing environments. Their flexibility, precision, and versatility make them ideal for a wide range of applications, and they are likely to continue to be an important part of industrial automation in the future.

In industrial applications, articulated robots can be used for a wide range of tasks, such as:

- **Assembly**: Robots can be used to assemble products with high precision and consistency, reducing errors and increasing efficiency.
- **Material handling**: Articulated robots are commonly used to handle and transport materials within a manufacturing facility, such as loading and unloading materials from conveyors or transporting materials between workstations.
- **Painting and coating**: Robots are used in industries such as automotive and aerospace to apply paint and other coatings with high precision and consistency, resulting in a high-quality finish.
- **Welding and cutting**: Articulated robots are used in welding and cutting applications, such as in the automotive and construction industries, to perform these tasks with high accuracy and efficiency.

Overall, the use of articulated robots in scientific research and industries is rapidly expanding, providing researchers with new tools and capabilities for exploring the frontiers of science and technology and manufacturers with capabilities for increasing efficiency, reducing costs, and improving product quality.

(Bayram & Ince, 2018) discusses how advances in information technology, such as artificial intelligence and Big Data, are changing the use and design of robots in the industry, particularly in the context of Industry 4.0. (Singh, Sellappan, & Kumaradhas, 2013) emphasizes the benefits of industrial robots, including speed, accuracy, cost reduction, waste reduction, and the creation of new job opportunities.

2.5.2 Collaborative robots

Collaborative industrial robots are specifically engineered to work alongside human operators within industrial settings. There are two distinct categories of collaborative robots. The first group includes robots intended for collaborative applications that adhere to the safety guidelines outlined in the International Organization for Standards (ISO) standard 10218-1. This standard defines the necessary safety measures, design criteria, and usage instructions for industrial robots to ensure their inherent safety. The second category encompasses collaborative robots designed for cooperative tasks but that do not meet the stipulated requirements of ISO 10218-1. It is essential to note that the absence of ISO 10218-1 compliance does not automatically indicate that these robots are unsafe. They may instead adhere to alternative safety standards, such as national regulations or in-house safety guidelines.

Considerable variation exists among the categories of collaborative robots that align with the specifications, as well as the extent of interaction between the robot and human operators in collaborative applications. On one end of the technological spectrum, we find traditional industrial robots functioning in separate workspaces. Workers can occasionally enter these workspaces without the need to power down the robot or secure the production area. These robots' workspaces can be equipped with sensors that detect human movements, ensuring that the robot operates at significantly reduced speeds or halts entirely when a worker is present within the designated area. On the opposite end of the spectrum, we encounter industrial robots expressly designed to operate alongside humans in a shared workspace. Often referred to as 'cobots,' these robots incorporate a range of technological features to guarantee that they do not pose any harm when a worker intentionally or accidentally comes into direct contact with them. These features include the use of lightweight materials, rounded contours, protective padding, 'skins' (padding embedded with sensors), and sensors positioned at the robot's joints. These sensors measure and regulate force and speed, ensuring that they never surpass predefined safety thresholds in case of contact.

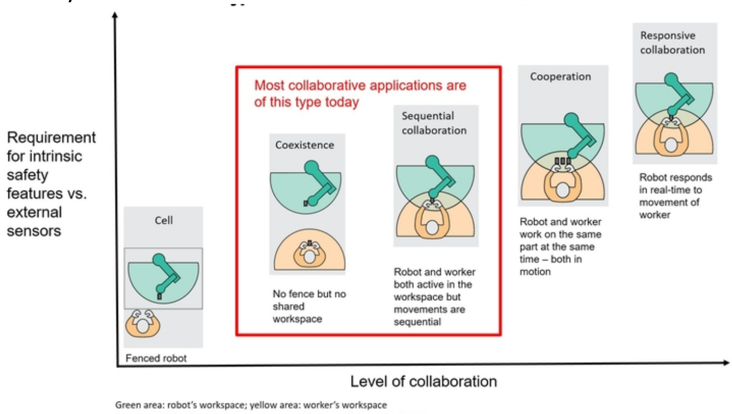


Figure 6. Types of collaboration with industrial robots (IFR, 2022)

To operate industrial robot as cobot, there are several solutions that are used to make robot work as cobot:

- **Safety-rated sensors**: Collaborative robots are equipped with safety-rated sensors such as light curtains, laser scanners, and force/torque sensors to detect human presence and ensure safe interaction.
- **End-of-arm tooling**: The robot's end-of-arm tooling can be designed with soft, compliant materials or force-limiting devices to reduce the risk of injury in the event of contact with a human worker.
- **Programming**: Collaborative robots can be programmed with advanced algorithms that allow them to detect and respond to human workers' movements, such as slowing down or stopping if a person enters the robot's workspace.
- **Separation monitoring**: Separation monitoring systems use cameras or sensors to detect the distance between the robot and human workers and alert the robot to slow down or stop if the separation distance is breached.
- **Shared control**: Shared control systems allow human workers to collaborate with the robot by providing input to the robot's movements, ensuring that the robot's actions align with the human's intentions.

In scientific literature, the use of collaborative robots is gaining increasing attention due to their potential to enhance productivity, efficiency and safety in manufacturing, logistics, and other industries. Collaborative robots can perform repetitive, dangerous, or physically demanding tasks, allowing human workers to focus on more complex or value-added activities. The use of collaborative robots is seen as a promising approach to address the challenges of labour shortage, skills gap, and increasing demand for customization and flexibility in modern manufacturing and logistics industries. (Matheson, Minto, Zampieri, Faccio, & Rosati, 2019) highlights the potential of cobots in making simple, quick, and cost-effective layout changes, while (Bragança, Costa, Castellucci, & Arezes, 2019) emphasizes the advantages of collaborative robots in supporting human workers with physical and cognitive tasks in Industry 4.0 environments. (Sherwani, Asad, & Ibrahim, 2020) further discusses how collaborative robots offer increased productivity, flexibility, versatility, and safety compared to traditional industrial robots.

The use of cobots is becoming increasingly common. The share of collaborative robots among all installed robots has been in a continuous growth trend as showed on figure 7.

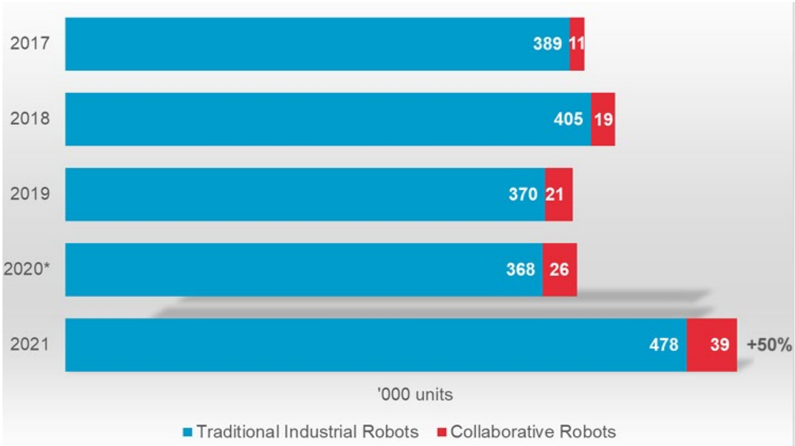


Figure 7. IFR World Robotics 2022 report. Annual installations of industrial robots - World (IFR, 2022)

2.6 Mobile robots

Mobile robots, also known as autonomous mobile robots (AMRs), are a type of industrial robot that can navigate and operate in unstructured environments. These robots are equipped with sensors, cameras, and other devices that allow them to move and navigate autonomously, without the need for human guidance. Mobile robots are used in a variety of industries, such as manufacturing, logistics, and healthcare, to transport goods, materials, and equipment.

The design of mobile robots is influenced by the environment in which they operate, such as indoor or outdoor, smooth, or rough terrain, and the presence of obstacles. Some robots are equipped with wheels or tracks, while others have legs or wings. The choice of locomotion method depends on the intended application and the constraints of the environment. Ground-based robots, such as automated guided vehicles (AGVs) and autonomous mobile platforms (AMPs), operate on wheels, tracks, or legs and are used to move heavy loads or navigate complex environments.

One of the main advantages of mobile robots is their flexibility and adaptability to different environments and tasks. They can be easily reprogrammed or reconfigured to perform different tasks or navigate different environments, making them ideal for dynamic and rapidly changing manufacturing or logistics environments. Mobile robots can also work collaboratively with human workers, providing support and assistance to improve efficiency and safety. (Kececi & Ceccarelli, 2015) emphasizes the importance of interaction with the environment and the acceptance of robotic systems in various human activities. (Angerer, Strassmair, Stähr, Roettenbacher, & Robertson, 2012) discusses the potential use of mobile assistive robots in automotive logistics and assembly applications, highlighting their flexibility and ability to support workers in tasks. (Unhelkar, Siu, & Shah, 2014) compares the performance of human and mobile robotic assistants in collaborative fetch-and-deliver tasks, finding that while there are differences in interaction times and subjective responses, mobile robotic assistants can effectively support human workers.

Future research in mobile robots is focused on improving their sensing and control capabilities, increasing their autonomy and adaptability, and enhancing their safety and reliability. These advancements will enable the deployment of robots in new and challenging applications. (Loganathan & Ahmad, 2023) provides a systematic review of recent advances in autonomous mobile robot navigation. It discusses the limitations of current navigation techniques and provides guidance for future research into creating new strategies that can enhance the autonomy level of AMRs while ensuring safety and reliability. (Raj & Kos, 2022) provides a comprehensive study of mobile robots, including their history, developments, applications, and future research perspectives. It discusses the architecture, components, and mechanism of mobile robots, as well as their impacts on artificial intelligence.

The use of mobile robots also presents some challenges, such as the need for advanced sensor and navigation technologies, and the development of safety standards and regulations for their use in shared workspaces with human workers. Overall, mobile robots are a promising technology that can improve the efficiency and safety of industrial processes in a variety of industries. (Markis A. , Papa, Kaselautzke, & Rathmair, 2019) emphasizes the complexity of mobile robotic systems and the need for safety standards and best practices to ensure their safe implementation. (Lehtinen, Kaarmila, Blom, Kauppi, & Kerva, 2000) discusses the evolution of autonomous vehicles in industrial settings and the potential for training robots to navigate office buildings. (Kragic, Gustafson, Karaoğuz, Jensfelt, & Krug, 2018) addresses the challenges of developing interactive and collaborative robots that can adapt to changing production needs and work alongside human workers. (Rajawat, et al., 2021) focuses on the importance of safety measures and regulations to facilitate safe collaboration between humans and robots in industrial environments.

Transporting a robot arm on the factory floor from one working station to another can be a challenging task, as these arms are often large, heavy, and require careful handling to avoid damage. Using a mobile robot for that purpose can be a solution and suitable approve need to be analysed. (Unger, Markert, & Müller, 2018) discusses the potential use cases and benefits of mounting static robots on mobile platforms in future factories. (Lottermoser, Berger, & Braunreuther, 2017) proposes a model for evaluating the usability of mobile robots in manufacturing environments. (Zhang, Martínez, Wang, Fuhlbrigge, & Eakins, 2010) describes a self-sufficient mobile platform for an industrial robot, emphasizing its ability to navigate various terrains and operate independently.

2.6.1 Mobile robots' navigation technologies

Mobile robots use various technologies for navigation, depending on the environment in which they operate and the desired level of autonomy. One of the key challenges in deploying mobile robots is navigation, which involves determining the robot's position and orientation relative to its environment and planning a trajectory to reach a destination.

Some of the commonly used technologies for robot navigation are:

- **Global Positioning System (GPS):** GPS is a satellite-based navigation system that provides location and time information. It is commonly used for outdoor navigation and requires an unobstructed view of the sky.
- **Inertial Navigation System (INS):** This involves using sensors such as accelerometers and gyroscopes to measure the robot's acceleration and rotation and estimate its position and orientation.
- **Odometry**: This involves using wheel encoders to measure the distance travelled by the robot and estimate its position.

- **LIDAR:** LIDAR (Light Detection and Ranging) uses laser beams to measure distances and create a 3D map of the environment. It is commonly used for obstacle detection and avoidance.
- **Ultrasonic sensors:** Ultrasonic sensors use sound waves to measure distances and detect obstacles. They are commonly used for close-range navigation and obstacle avoidance.
- **Magnetic sensors:** Magnetic sensors measure the magnetic field of electrified wire and use it to estimate the robot's orientation. They are commonly used for indoor navigation, where GPS signals may not be available.
- **Radio Frequency Identification (RFID):** RFID tags are placed in the environment, and the robot uses an RFID reader to navigate to specific locations. It is commonly used for indoor navigation and asset tracking.

The selection of navigation technology depends on the robot's application and the environment in which it operates. Many robots use a combination of these technologies to achieve robust and accurate navigation. (Blaha & Gerig, 1994) highlights the use of a combination of an INS and sensors for accurate navigation in small areas. (Sprunk, Lau, Pfaff, & Burgard, 2017) focuses on an accurate navigation system designed specifically for omnidirectional robots in industrial environments, considering safety and efficiency. (Gul, Rahiman, & Alhady, 2019) provides a comprehensive study of various navigation techniques suitable for both static and dynamic environments.

Simultaneous Localization and Mapping (SLAM) is a navigation technology that enables mobile robots to build a map of their environment and simultaneously determine their location within that map. This is achieved by using various sensors such as cameras, LiDAR, and/or sonar to gather information about the robot's surroundings, and then processing that information in real-time to create a map of the environment (Bresson, Alsayed, Yu, & Glaser, 2017) explores the evolving landscape of Simultaneous Localization And Mapping (SLAM) in the context of autonomous driving. (Tsubouchi, 2019) introduces SLAM as a core technology for mobile robots, emphasizing its role in creating maps of the environment and estimating the robot's position. (Wei & Li, 2021) provides an overview of visual SLAM, highlighting its importance in autonomous mobile robots and autonomous vehicle navigation.

SLAM algorithms typically use a probabilistic approach, where the robot's location and the location of surrounding objects are represented as probability distributions. As the robot moves, its sensors detect changes in the environment and the probability distributions are updated, resulting in a more accurate map and localization estimate. SLAM has become an important technology for mobile robotics in a variety of applications, including warehouse logistics, autonomous vehicles, and search and rescue missions. It enables mobile robots to navigate in complex environments without relying on pre-existing maps, making them more versatile and adaptable to changing environments.

2.7 Machine vision

Machine vision is a technology that allows machines to interpret and understand visual information from images or video. It involves the use of various techniques such as image processing, pattern recognition, and machine learning to analyse and extract useful information from images or videos. The information obtained can be used for a variety of applications such as quality control, inspection, identification, and tracking.

Machine vision systems consist of various components, such as cameras, image sensors, lenses, lighting, and image processing software. The cameras capture images or videos of the objects, which are then processed by the image processing software to extract features such as edges, corners, and textures. These features are then analysed using pattern recognition algorithms to identify and classify the objects.

One of the key advantages of machine vision is its ability to perform repetitive and complex tasks with high accuracy and speed. It is also versatile and can be used in a wide range of applications. In manufacturing, machine vision is used for quality control, inspection, and defect detection. It can identify defects in products such as scratches, cracks, and discoloration. (Simpson, 2003) explores the suitability of vision in automated assembly tasks and the potential benefits of distributing vision throughout the assembly process. (Benbarrad, Salhaoui, & Kenitar, 2020) focuses on the role of machine vision in Industry 4.0, highlighting its use in quality control, defect identification, and predictive analysis for process improvement.

Industrial robots can be integrated with machine vision systems to enhance their functionality, precision, and position (Figure 8). Machine vision systems can provide robots with real-time feedback on their work environment, enabling them to make intelligent decisions about their actions. For instance, machine vision can help industrial robots detect and recognize objects, measure their position and orientation, and adjust their movements accordingly.

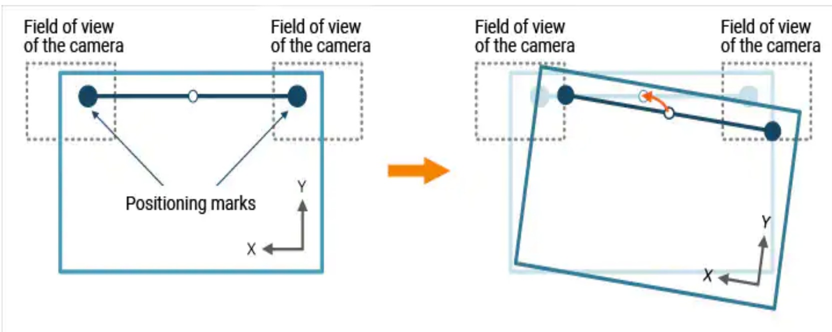


Figure 8. Position deviation detection (Keyence.com, 2023).

Several articles discuss various aspects of the relationship between industrial robots and machine vision, such as vision-guided robotics, robotic grasping using vision, and autonomous robotic assembly using machine vision techniques. (Pérez, Rodríguez, Rodríguez, Usamentiaga, & García, 2016) provides a comparative review of different machine vision techniques for robot guidance in industrial environments. (Yang, 2021) focuses on the application and improvement measures of industrial robot grasping technology based on machine vision. (Xie, 2023) discusses the design of an industrial robot assembly line using machine vision, including obstacle detection and path planning. For example, robots can be used to move cameras to different locations in a manufacturing plant, allowing them to capture images from various angles and distances. Robots can also be programmed to perform specific tasks based on the data collected by machine vision systems.

The integration of industrial robots and machine vision systems represents a powerful solution for improving the efficiency and quality of manufacturing operations. Machine vision is a rapidly growing field with many potential applications. Its ability to interpret and understand visual information has the potential to revolutionize many industries and improve the efficiency and accuracy of various processes.

2.8 IoT and M2M

IoT is a network of interconnected devices, sensors, and systems that communicate with each other to enable the exchange of data and information. IoT is a growing field that is expected to revolutionize the way we interact with technology. Machine-to-Machine (M2M) technology is a subset of IoT that enables devices to communicate with each other without the need for human intervention. IoT and M2M technologies are critical components of modern industrial systems. They enable the collection and analysis of vast amounts of data in real-time, allowing businesses to optimize their operations and make informed decisions. In the context of Industry 4.0, IoT and M2M technologies are essential for enabling the creation of smart factories and intelligent manufacturing systems (Gilchrist, 2018).

IoT and M2M technologies are closely related to industrial robots and play a significant role in enabling smart factories and Industry 4.0. Industrial robots can be connected to the internet, to each other and other machines through IoT and M2M technologies, creating a network of interconnected devices and systems. (Zentay & Mies, 2020) emphasizes the importance of holistic integration in Industry 4.0, including the integration of smart machines and collaborative robots. (Tsigie & Dagnaw, 2021) highlights how IoT and robotic systems are driving technological innovation and improving various aspects of manufacturing. (Liu & Zhong, 2017) discusses how IoT-enabled manufacturing supports smart factories and real-time decision-making in the context of Industry 4.0. (Martikkala, Davida, Lobovb, Lanza, & Ituartea, 2021) highlights that growing versatility and development speed of open-source IoT tools make them increasingly viable for industrial solutions, despite remaining challenges such as ease of use and regulatory compliance.

IoT and M2M technologies play a critical role in enabling the digital transformation of industries. They are essential for creating intelligent systems that can optimize operations, reduce costs, and improve efficiency. The integration of IoT and M2M technologies with industrial robots is crucial for the development of smart factories and the realization of the full potential of Industry 4.0.

2.9 Robotization overview

According to a report by the International Federation of Robotics (IFR), there were over 3.47 million industrial robots in operation worldwide in 2021, with articulated robots accounting for approximately 70% of the total. New installations in 2021 where the highest number in history, 517 000 new units where installed (IFR, 2022).

In terms of geographical distribution, Asia is the largest market for articulated robots, accounting for approximately 70% of global sales in 2021. China has been the world's largest industrial robot market since 2013 and accounted for 52% of total installations in 2021, followed by Japan and South Korea. The automotive industry is the largest user of articulated robots, accounting for approximately 40% of total sales, followed by the electronics industry and metal industry (IFR, 2022).

The use of articulated robots is expected to continue to grow in the coming years, driven by increasing demand for automation and the adoption of Industry 4.0 technologies. The IFR predicts that global sales of industrial robots will continue to increase at an average annual rate of approximately 12% (IFR, 2022).

Europe is the second-largest market for industrial robots, accounting for approximately 28% of global sales in 2019. The use of articulated robots is widespread across a range of industries in Europe, including automotive, electronics, and metalworking. Germany is the largest market for industrial robots in Europe, accounting for approximately 35% of total sales in the region. Other major markets in Europe include Italy, France, and the United Kingdom (IFR, 2022).

The automotive industry is the largest user of articulated robots in Europe, accounting for approximately 40% of total sales, followed by the metal industry and the electronics industry. The use of robots in the food and beverage industry is also increasing in Europe, driven by the need for greater efficiency and safety.

In general, larger companies tend to have a higher adoption rate of industrial robots due to their higher investment capacity and economies of scale. In contrast, SMEs may have limited resources and face higher initial costs and technical barriers to adopting industrial robots. Nonetheless, there has been a growing trend towards the adoption of industrial robots among SMEs in recent years, driven by advancements in technology, lower costs, and increasing awareness of the benefits of automation.

The adoption of Industry 4.0 technologies is driving the increased use of articulated robots in Europe, as companies seek to improve their competitiveness and productivity. The IFR predicts that the use of robots in Europe will continue to grow in the coming years, driven by increasing demand for automation and the need for greater flexibility and efficiency in manufacturing.

2.9.1 Robotization among SMEs

The use of industrial robots is becoming increasingly popular among small and medium-sized enterprises (SMEs) as they seek to improve their productivity, quality, and competitiveness. While the initial investment in robotics technology can be high, the benefits of increased automation can result in significant cost savings over time, as well as increased efficiency and flexibility in manufacturing processes.

The adoption of robots in SMEs is driven by the need to remain competitive, increase productivity, and reduce labour costs. However, the adoption of robots among SMEs has been slow due to various reasons such as the initial investment cost, lack of technical expertise, lack of job for a robot and fear of job displacement. (Hedelind, Hellström, & Jackson, 2008) discusses the challenges faced by SMEs in sustaining success in the manufacturing industry and investigates a mobile, flexible, and reconfigurable robot solution. (Perzylo, Rickert, & Kahl, 2019) highlights the need for agile production environments and the introduction of cognitive abilities into robotic and automation systems to enable lean changeover and seamless human-robot collaboration. (Epping & Zhang, 2018) focuses on the challenges faced by SMEs in implementing industrial robotics and presents a sustainable decision-making framework for transitioning to robotic welding. (Kangru, Riives, Mahmood, & Otto, 2019) evaluation method allows assessing the profitability of the implemented production unit and obtaining additional economic and technical information for the development of future robotic production units.

The use of collaborative robots, or cobots, is also growing in popularity among SMEs. These robots are designed to work safely alongside human workers, allowing SMEs to introduce automation into their manufacturing processes without the need for extensive safety measures. (Vojić, 2020) highlights that collaborative industrial robots are affordable, easy to use, and can automate tasks such as quality inspection and pick-and-place. (Gualtieri, Palomba, Wehrle, & Vidoni, 2020) emphasizes the importance of implementing safety and ergonomics in human-robot collaboration to ensure successful integration in SMEs. (Bolmsjö, Danielsson, & Svensson, 2012) discusses the benefits of collaboration between operators and robots in flexible manufacturing systems, enabling automation in complex and low-volume tasks. (Matheson, Minto, Zampieri, Faccio, & Rosati, 2019) provides an overview of collaborative robotics in manufacturing applications, emphasizing the potential and advantages of cobots in terms of flexibility and layout changes.

Also, the use of mobile robots is becoming increasingly popular among SMEs as they seek to improve their efficiency, productivity, and flexibility in manufacturing and logistics processes. Mobile robots are autonomous or semi-autonomous robots that can move freely around a workspace or facility, carrying out tasks such as material handling, transportation, and inspection. Their ability to work alongside human workers, enhancing collaboration and improving safety in the workplace. Mobile robots are relatively easy to implement and operate, with many models designed for plug-and-play operation. This makes them a cost-effective solution for SMEs with limited technical expertise and resources. (Pieskä, Kaarela, & Saukko, 2012) highlights the need for easier human-robot interaction in SMEs and presents examples of how cognitive infocommunication can be utilized in robotics. (Ballestar, Díaz-Chao, Sainz, & Torrent-Sellens, 2020) finds that robotic devices are associated with higher productivity and employment rates in SMEs. (Hedelind, Hellström, & Jackson, 2008) investigates a mobile, flexible, and reconfigurable robot solution for SMEs. (Perzylo, Rickert, & Kahl, 2019) emphasizes the importance of introducing cognitive abilities into robotic systems for seamless human-robot collaboration in agile production environments.

Overall, the use of mobile robots among SMEs is increasing, driven by the need for increased efficiency, flexibility, and competitiveness in manufacturing and logistics. Advances in robotics technology and the availability of cost-effective solutions are making it easier for SMEs to adopt industrial robots and mobile robots in their operations, improving productivity and reducing costs. As mobile robot technology continues to evolve and become more accessible to SMEs, it is likely that we will see an increase in their adoption and use in the manufacturing industry.

There are several factors that may be hindering SMEs from adopting more robots in their operations, including:

- **Cost**: The initial investment in robotics technology can be high, which can be a significant barrier for SMEs with limited financial resources.
- **Lack of technical expertise**: Implementing and maintaining robotics technology requires specialized technical knowledge and skills, which may be difficult for SMEs to acquire and retain.
- **Integration with existing systems**: Integrating robotics technology with existing systems and processes can be challenging and time-consuming, which can deter SMEs from adopting robotics technology.
- **Safety concerns**: Ensuring the safety of workers and the workplace is a critical consideration when implementing robotics technology, which can be particularly challenging for SMEs with limited resources.
- **Resistance to change**: SMEs may be resistant to change and may prefer to maintain their existing methods and processes, even if they are less efficient.

2.9.2 Lack of job for a robot

Integrating the robot into the current system may bring attention to an issue: insufficient tasks for the robot in a particular position. The primary cause of underutilization of robots in manufacturing lies in the scarcity of tasks for robots in a specific location. (Vaher, Kangru, Otto, & Riives, 2019) research shows that SMEs production batches are small and rotation of different parts to produce is high. To address the underutilization of industrial robots in SMEs, potential countermeasures involve enhancing robot flexibility and adaptability to various tasks. This includes the development of more versatile robots and the establishment of networks where robots can collaboratively share workloads. (Dario Antonelli, 2016) proposes a human-robot collaboration paradigm where tasks are assigned based on batch size and programming complexity, demonstrating its applicability in small batch production.

The fact that SMEs may not have enough work for a robot is not necessarily a problem. (Perzylo A. , Rickert, Kahl, & Somani, 2019) highlights the need for agile production environments and the introduction of cognitive abilities in robotic systems. (Kragic, Gustafson, Karaoğuz, Jensfelt, & Krug, 2018) discusses the challenges of developing flexible solutions for quickly re-planning and adapting production lines. (Hedelind, Hellström, & Jackson, 2008) emphasizes the importance of mobile, flexible, and reconfigurable robot solutions in the face of changing business environments. Also, robots, particularly mobile robots, can be redeployed to different areas of the manufacturing or logistics process as needed, depending on the workload. In fact, the ability to redeploy robots is one of the advantages of robotics technology for SMEs. Unlike traditional fixed automation solutions, robots can be moved to different areas of the facility, allowing SMEs to adjust to changes quickly and easily in demand and production needs.

While the fact that SMEs may not have enough work for a robot at one fixed position may require some adjustments to the manufacturing or logistics process, it is not necessarily a significant barrier to the adoption of robotics technology. Instead, it is important for SMEs to consider the potential benefits of using robots and to determine how robotics technology can best be integrated into their operations.

The use of robots in a fixed workplace may turn out to have a very low utilization rate due to the lack of work at a given machine. In the case of SMEs, work batches are often small. With one production machine, situations may arise where the machine is idle and therefore the robot too. With the more efficient use of robots and cooperation robots, it is possible to increase their utilization rate to more than 90% (IFR Case Studies, 2022).

2.10 Different approaches

The exploration of mobile robots presents a promising avenue for revolutionizing the operational landscape within small and medium-sized enterprises (SMEs). This study delves into the potential of mobile robots to significantly enhance both efficiency and adaptability within robotic systems tailored for SMEs. The primary focus lies in investigating the autonomous and flexible material handling capabilities of mobile robots, with a particular emphasis on the conceivable transportation of robot arms between various workstations. (Melo & Corneal, 2020) presents a case study evaluating the automation of material handling with mobile robots, demonstrating the benefits of material flow improvements and layout optimization using mobile robots. (Lehtinen, Kaarmila, Blom, Kauppi, & Kerva, 2000) discusses the development of autonomous vehicles for industrial applications, including office buildings. (Chao, Zhou, & Xu, 2013) discusses a mobile robotic control system that incorporates a master-slave teleoperate mechanical arm, allowing the robot to perform intricate tasks in complex work environments. (Yusoff, Samin, & Ibrahim, 2012) focuses on the development of a wireless mobile robot arm controlled by a wireless PS2 controller, enabling pick and place operations. (Salama, Hassanien, Hassanien, & Hefny, 2020) explored the use of mobile robots to transport materials and products between different workstations in a smart factory, which led to a reduction in production time and cost. (Sun, 2018) discusses how the use of a mobile robot arm in a manufacturing setting can increase production efficiency by reducing the need for human labour and improving the flexibility and speed of production processes. These studies suggest that the integration of mobile robots and robot arms into production systems can lead to significant improvements in production efficiency and cost-effectiveness.

The studies mentioned earlier primarily focused on the use of mobile robots for transporting robot arms to different locations within a manufacturing facility to increase the utilization of the robot arm. However, some of these studies also discussed the accuracy of the solution. For example, (Röwekämper, et al., 2012) demonstrates that by combining components such as Monte-Carlo localization and scan matching, a few millimetres of accuracy can be achieved at taught-in reference locations. (Eren, Fung, & Nakazato, 1995) presents a system based on coded infrared signal transmission that substantially improves position estimation accuracy through a multi-sensor arrangement on the robot. (Wang, Liang, & Maropoulos, 2011) introduces a method utilizing external large volume metrology instruments, such as laser trackers or iGPS, to achieve high accuracy positioning and simplify navigation for mobile robots.

On the market there are already many commercial solutions available as showed on figure 9. Most of them are solutions where mobile robot and robot arm are connected permanently together. It means that robot arm positioning accuracy is good as it is for the mobile robot, and it is worse than robot arm accuracy. This approach enables the efficient utilization of a robot arm to execute diverse tasks across different locations. Nevertheless, it is essential to acknowledge that the cost of this solution encompasses the expenses of two separate robots - a robot arm and a mobile robot. This approach is justified when the primary objective of the robot system involves constant movement between different tasks, which necessitates the use of the robot arm. A vast majority of robot arm applications involve machine servicing, palletizing, and packaging, which are localized tasks. Consequently, while the robot arm is engaged in its operations, the mobile robot remains idle, unable to perform other tasks simultaneously. This use of resources is not optimal for efficient utilization.

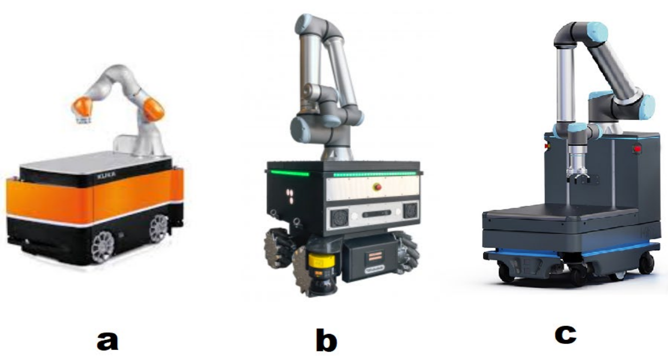


Figure 9. Different solutions on the market. Kuka (a), Robotnik and UR (b), MIR and UR (c).

A critical factor to consider is the positioning accuracy of the mobile robot in this context. While robot arms possess high precision, the same cannot be said of mobile robots. Depending on the specific solution employed, the accuracy gap between the two can range from 10 to 100 times. Consequently, the tasks that a given robot system can perform are determined by the accuracy of the repositioning of the mobile robot. Without additional calibration of the robot arm, the precision of the mobile robot may not be sufficient to enable the robot arm to perform the tasks it was primarily designed to execute.

2.11 Standards

In the realm of industrial automation, there are several established standards and frameworks that organizations follow to ensure efficient and effective automation of processes. Some of the well-known standards include:

- ISO 8373:2021 Robotics — Vocabulary:
  - Provides a standardized vocabulary for the field of robotics.
  - Relevant to industry robotization by ensuring a common understanding of terms and definitions across the industry. This helps in effective communication and collaboration among professionals involved in robotization.
- ISO 10218:2011 Robots and robotic devices:
  - Specifies safety requirements for industrial robots.
  - Essential for industry robotization to ensure the safety of human operators and others working in proximity to robots.
- Machinery Directive (2006/42/EC):
  - The directive sets out essential health and safety requirements that machinery, including robots, must meet.
  - To be placed on the EU market, machinery, including industrial robots, must bear the CE marking, indicating compliance with the Machinery Directive. This involves a process of conformity assessment to demonstrate adherence to safety requirements.
  - Manufacturers of machinery, including robotics manufacturers, are required to prepare technical documentation that demonstrates compliance with the essential health and safety requirements. This documentation should be available for inspection by relevant authorities.
  - The Machinery Directive is applicable not only to the manufacture of robots but also to their installation and integration into production processes. Integrators and users are responsible for ensuring that installed robots comply with safety requirements.
- ISA-95 (Enterprise-Control System Integration):
  - Defines models and terminology for the integration of enterprise and control systems.
  - Critical for industry robotization as it facilitates seamless integration between different levels of control systems, optimizing the overall efficiency of industrial processes.
- IEC 61131 (Programming languages for programmable logic controllers):
  - Defines standard programming languages for programmable logic controllers (PLCs).

    - Significant for industry robotization by providing a standardized approach to programming PLCs, enhancing interoperability and ease of integration in automated systems.
- IEC 61499 (Function blocks for distributed control systems):
    - Defines standards for function blocks in distributed control systems.
    - Important for industry robotization as it enables the development of modular and scalable control systems, enhancing flexibility and adaptability in automated processes.
- IEC 62264 (Levels of Automation):
    - Specifies levels of automation in manufacturing systems.
    - Relevant to industry robotization by providing a framework for understanding and implementing automation levels, aiding in the design and optimization of automated processes.
- ISO 9001 (Quality Management Systems):
    - Sets the criteria for a quality management system.
    - Crucial for industry robotization as it ensures a systematic approach to quality, promoting consistency and reliability in manufacturing processes.
- ISA-18/IEC 62682 (Management of alarm systems for the process industries):
    - Addresses the management of alarm systems in the process industries.
    - Important for industry robotization by providing guidelines for effective alarm management, minimizing disruptions, and ensuring safe operation.
- ISA-84/IEC 61511 (Functional safety: Safety instrumented systems):
    - Specifies requirements for the design and implementation of safety instrumented systems.
    - Essential for industry robotization to ensure the safety of automated processes, especially in critical applications.
- ISA-88/IEC 61512 (Batch control systems):
    - Defines standards for batch control systems.
    - Relevant for industries employing batch processing in their operations, ensuring consistency and efficiency in automated batch processes.
- ISA-99/IEC 62443 (Cybersecurity for industrial automation and control systems):
    - Addresses cybersecurity for industrial automation and control systems.
    - Critical for industry robotization to protect automated systems from cyber threats, ensuring the integrity and security of industrial processes.
- ISA-100/IEC 62734 (Wireless systems for automation):
    - Specifies standards for wireless systems in automation.
    - Important for industry robotization as it facilitates the integration of wireless communication technologies, enabling flexibility and mobility in automated systems.
- ISA-100 (Human-machine interfaces for process automation systems):
    - Addresses standards for human-machine interfaces in process automation.
    - Relevant for industry robotization by providing guidelines for user interfaces, enhancing the usability and efficiency of human-robot interactions.
- ISA-108 (Intelligent device management):
    - Defines standards for the management of intelligent devices.
    - Important for industry robotization as it provides guidelines for the effective management and maintenance of intelligent devices used in automated systems.

There are standards that describe industrial systems automation levels. One of the most widely recognized standards for this purpose is the ISA-95 standard, officially known as ANSI/ISA-95, or "Enterprise-Control System Integration." This standard was developed by the International Society of Automation (ISA) and the American National Standards Institute (ANSI). The ISA-95 standard provides a framework for integrating enterprise-level business systems with control systems in industrial automation environments. It defines five levels of automation in an industrial system, known as "levels of the automation pyramid."

The ISA-95 standard helps in defining the scope and responsibilities of different automation levels, promoting interoperability between various systems, and facilitating effective communication and data exchange within an industrial automation environment. It provides a structured approach for system integration, enabling companies to achieve seamless and efficient operation across all levels of their industrial automation systems.

The ISA-95 standard does not specifically describe levels of automation. Another standard that does describe levels of automation in industrial systems is the "Levels of Automation (LOA)" standard, also known as the IEC 62264-1 standard. This standard is part of the IEC 62264 series, developed by the International Electrotechnical Commission (IEC), and it focuses on the integration of enterprise and control systems in the process industry. The IEC 62264-1 standard defines three levels of automation, known as "LOA Levels". The IEC 62264-1 standard provides a framework for understanding the different levels of automation in industrial systems and how they interact to achieve a cohesive and efficient manufacturing process. It facilitates communication between the various levels and promotes a common understanding of automation within the process industry.

Machinery Directive in the EU is crucial for the field of robotics, as it establishes safety standards and requirements that must be met by manufacturers, integrators, and users of industrial robots placed on the European market. Compliance with the directive is essential for ensuring the safety of workers and others interacting with robotic systems.

2.12 Summary

In the realm of technology integration, numerous possibilities arise for small and medium-sized enterprises (SMEs). The ease with which various technologies can be integrated presents an opportunity to devise new solutions, fostering a smoother and more rapid adoption of technologies. This adaptability allows companies to stay agile in the face of the ever-changing technological landscape, ultimately bolstering their competitiveness in the market.

The seamless integration of different technologies not only enables companies to implement solutions that precisely align with their specific needs and objectives but also opens the door to the creation of novel and more efficient business models and processes. This enhanced technological flexibility positions companies to be more resilient and sustainable in the dynamic technological environment. Hence, it is crucial to recognize and explore the potential of integrating technologies to support innovation within SMEs, contributing to their successful technological development.

Within the context of this study, the literature review further underscores the importance of integration, emphasizing that the amalgamation of various technologies can be streamlined through standardization and the utilization of uniform protocols. This approach facilitates the creation of innovative and tailored solutions, effectively addressing specific and, at times, highly specialized challenges faced by companies. The convergence of technologies, as highlighted in the literature, provides a unique opportunity for companies to develop distinctive problem-solving approaches.

The study also advocates for the embrace of novel technologies, emphasizing that doing so enables companies to not only address challenges more effectively but also enhances their operational efficiency. By acknowledging the synergies between disparate products and technologies, companies can forge a path toward improved adaptability, efficiency, and innovation in the rapidly evolving technological landscape.

In summary of the literature review, it becomes evident that a plenty of novel technologies and technological solutions exist for industries and process management. Several of these technologies remain relatively nascent, and their widespread adoption is yet to encompass all companies. For instance, Industry 5.0 revolves around self-learning systems empowered by AI, which, presently, may not find extensive utilization among many small and medium-sized enterprises.

3 Research on the use of a flexible robot solution

Manufacturing has been revolutionized with the adoption of industrial robots. The use of industrial robots has resulted in increased efficiency, improved quality, and reduced labour costs for manufacturers.

Looking ahead, the manufacturing industry is expected to continue to grow and evolve with the adoption of new technologies such as AI, IoT, and Industry 4.0 principles. These technologies will enable more flexible and connected manufacturing systems, which will further improve efficiency and productivity.

In terms of industrial robots, the focus is shifting towards collaborative robots (cobots) that work alongside humans and are designed to be easily programmed and deployed. These cobots are expected to increase safety, flexibility, and productivity in manufacturing processes.

3.1 Outcomes of a survey

(Vaher, Kangru, Otto, & Riives, 2019) wrote a report on the outcomes of a survey among Estonian companies, which highlighted that small and medium-sized enterprises (SMEs) typically have small and highly variable production batches, and machine tool utilization rates are not typically high across most firms. Only one-quarter of the companies surveyed reported workbench utilization rates exceeding 75 %, with most firms reporting average usage rates near 50 %, shown on figure 10. About 30 enterprises took part in the survey. The average number of employees of the enterprises was 140 people, and according to turnover data, most of the companies could be defined as SMEs (small and middle-sized enterprises).

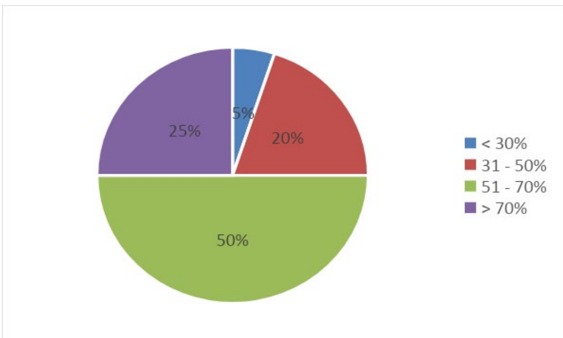


Figure 10. OEE among SME's (Vaher, Kangru, Otto, & Riives, 2019)

The survey included questions about batch/lot sizes of products and parts, and about the repeatability factor of a batch – meaning whether one part is produced multiple times or is every operation different. The survey showed that the batch sizes in 1/3 of the enterprises correspond to 10 – 50 units as shown on figure 9, left side graph. In most cases, the repeatability of a batch was more than 50%. In case of batch sizes of less than 10 units, we could see a low repeatability level (ca 10%). With batches of more than 50 units, the repeatability level was high, more than 50%. Over 60% of company's answer that more that 50% of batches are repeated constantly over the time as shown on figure 11, right side graph.

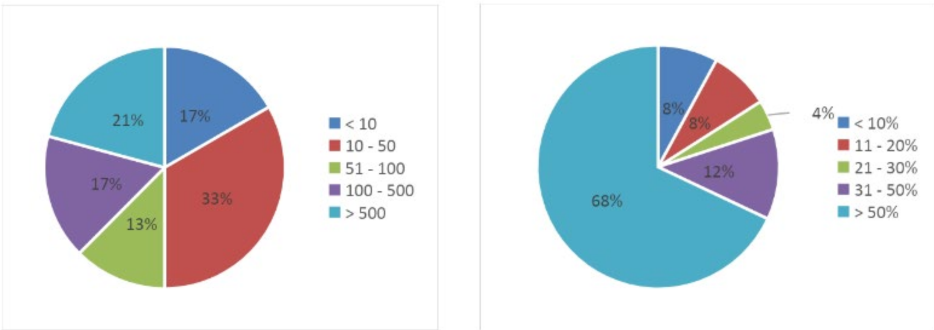


Figure 11. Parts in lot size (left) and repeatability of the lots (right) (Vaher, Kangru, Otto, & Riives, 2019).

The survey by (Vaher, Kangru, Otto, & Riives, 2019) conducted among Estonian enterprises shows that the robots used in production are mainly welding robots which are not used to their 100% capacity as shown on figure 12. At the same time, enterprises would like to use robots for other operations as well. The problem is that it is difficult to implement welding robots for other tasks, as their tool and installation is meant only for welding operations, and it would be too costly to exchange those. Instead, it would be feasible to use a new robot for operations other than welding. In case the new robot cannot be fully occupied with one type of task, it would be beneficial to find a universal solution where the robot could perform different types of tasks, such as serving the CNC bench, material handling and packaging.

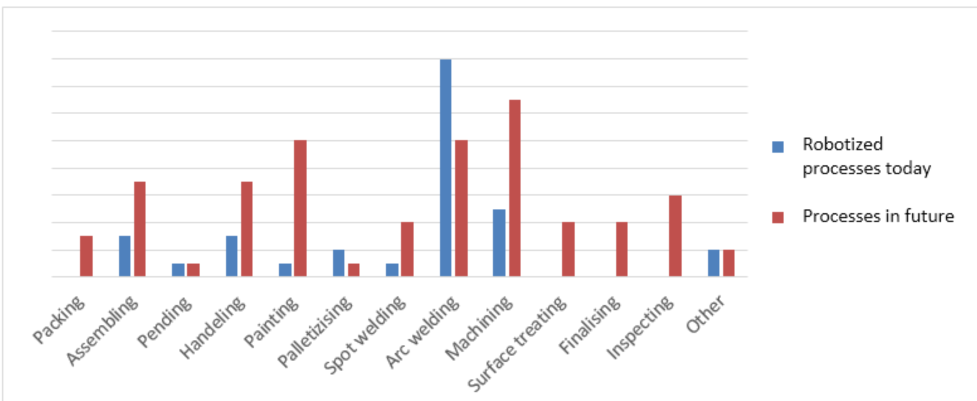


Figure 12. Robotized processes today and wanted processes in future among Estonian companies (Vaher, Kangru, Otto, & Riives, 2019).

3.2 New approach is needed

Given such production characteristics, permanent integration of a robot into the workstation is impractical. Downtime of the robot arm will be too long, and utilisation of the robot is very low. Mobile robots carrying a robot arm from one position to another, as shown on figure 9, is too expensive solution for SMEs. One of the downsides of this solution is that the two robots (two resources) can never work simultaneously.

Regardless of the type of a work tool of a robotic arm, the more important question is whether to bring the work tasks to the robot or to take the robot go to the task. It is important to assess whether and how much will the system be reorganized and how much additional investments will be needed.

It was further concluded that the device comprising a mobile robot and a robot arm should be separated into two distinct resources as shown in figure 13. However, it is recommended to maintain the autonomous transport of the robot arm between different workstations.

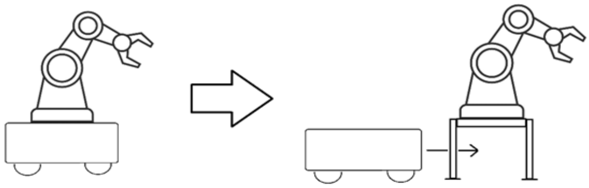


Figure 13. Separating robot arm from mobile robot (Vaher, Kangru, Otto, & Riives, 2019).

3.3 Building the testbed

To confirm the hypothesis and the results of the theoretical analysis, practical tests were carried out at the TTK UAS Tallinn University of Technology. For this purpose, a miniature production operating on the principles of Industry 4.0 was built (shown on figure 14), where several CPS solutions are used where software and hardware components are seamlessly integrated towards performing well defined tasks (Vaher, Vainola, Otto, & Riives, 2019) (Moor, Vaher, Riives, Kangru, & Otto, 2021).

Figure 14. Industry 4.0 testbed at TTK University of Applied Sciences (Tallinn).

The entire system operates autonomously, leveraging advanced principles from the fields of Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and Machine-to-Machine (M2M) communication. Within this framework, incoming orders are meticulously orchestrated within the ERP system, which serves as the foundational platform for planning and scheduling production activities. At the heart of this operational orchestration lies the MES program, meticulously crafted to manage the intricate sequence of production operations. This MES program operates at a granular level, overseeing the flow of tasks and resources with a precision that optimizes efficiency and minimizes downtime. Through seamless M2M communication protocols, the MES program coordinates the actions of various devices within the production environment, ensuring a synchronized workflow. Each device within the system is intricately connected to the MES via LAN or Wi-Fi, facilitating real-time data exchange and control. However, it's noteworthy that these devices function independently of one another, thanks to the robust autonomy ingrained in their design. This autonomy enables them to execute their designated tasks without necessitating constant communication with a higher-level program, thereby enhancing reliability and resilience in the face of potential network disruptions or system failures as shown on figure 15.

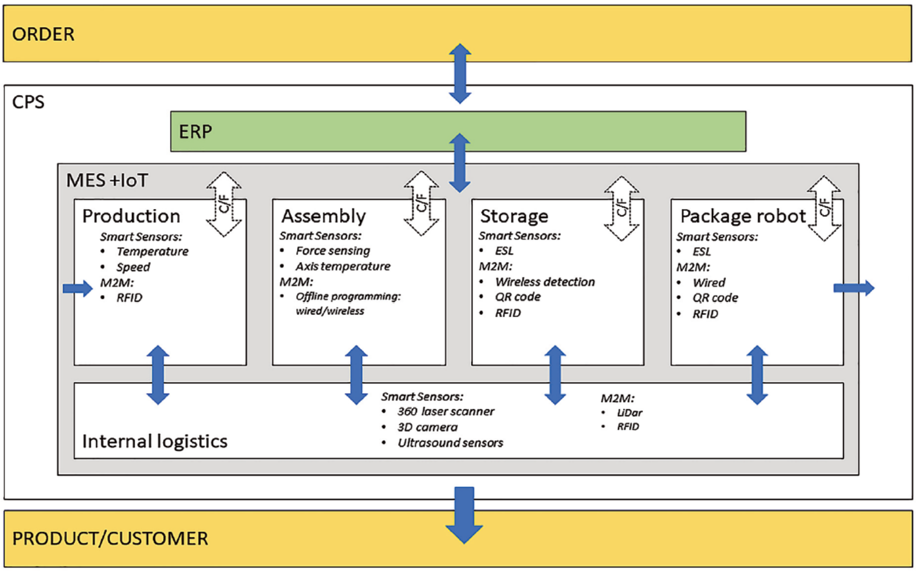


Figure 15. Developed systems schematic diagram (Moor, Vaher, Riives, Kangru, & Otto, 2021).

3.3.1 Design of architecture

The hardware architecture is configured in a manner wherein the Manufacturing Execution System (MES) operates on a dedicated server located within the laboratory premises. This server is intricately interconnected with the school's network infrastructure on one side and the laboratory's internal network, namely the intranet, on the other. The internal network of the laboratory comprises a Wi-Fi router along with two switches, one of which supports Power over Ethernet (PoE) functionality. Devices or robots within the system are interconnected to these switches either through direct cable connections or wirelessly via the router's Wi-Fi capability. Each device within the system is assigned a fixed IP address to facilitate seamless communication and control. Preferably, these IP addresses are configured dynamically by the Wi-Fi router based on the devices' unique Media Access Control (MAC) addresses, or alternatively set statically on the devices themselves for enhanced stability and predictability in network communication.

The software architecture is such that the Central Software Business Logic resides in the Tktk.Mes project and runs as an ASP.net Core 2 project on the server on top of IIS. The central software includes a website-based founder interface (Angular 6) and an API layer. Both the user interface, the device manager server and the periodic job launcher interact with the API layer. Data is stored in a Microsoft SQL 2017 Express database.

For each distinct device within the system, a dedicated project is developed to facilitate communication, ensuring specialized handling tailored to the unique requirements of each device. These projects are named accordingly, such as Tktk.Device.Mir, Tktk.Device.Pharoah, and so forth, with each possessing the requisite knowledge and protocols for effective interaction with its designated device.

Operational as Windows services on the server, these device-specific projects exclusively engage in information exchange with a central entity known as the device manager, represented by the Tktk.Device.Server project, which also operates as a Windows service. This structured communication framework ensures that all pertinent information flows through a centralized hub, enhancing system efficiency and coherence. The communication between these Windows services is facilitated through the MQTT (Message Queuing Telemetry Transport) protocol, a lightweight and efficient messaging protocol ideal for IoT (Internet of Things) environments. Management of MQTT communications is overseen by the Tktk.Device.Broker project, which operates as a Windows service, orchestrating the seamless flow of data between the various device projects and the device manager. Interaction with the broader business logic layer, encapsulated within the central software API, is exclusively managed by the device manager. However, an exception is made for human operatives within the MES, who have the capability to communicate both with the equipment manager and directly with the API layer for enhanced usability and flexibility in operational tasks. This dual communication pathway facilitates a more intuitive and streamlined interface for human operators interfacing with the system. All Windows service projects are implemented with the Topshelf framework. All logging is performed on the Serilog framework.

3.3.2 System logic

The design of the system's logic is rooted in the principle of fault tolerance, where the failure of one device or the occurrence of an error is meticulously isolated to prevent cascading effects on the operation of other devices. This resilience is achieved through a carefully engineered architecture that ensures each device operates independently within its designated scope, even in the face of adverse events. Within this seamlessly integrated framework, the factory operates around the clock, 365 days a year, boasting a remarkable 100% automation rate.

However, contrary to the misconception that automation entirely excludes human involvement, this innovative solution embraces human-machine collaboration. Here, individuals are empowered to undertake tasks traditionally associated with robotic automation, showcasing the versatility and adaptability of the system. This symbiotic relationship between humans and machines not only enhances operational flexibility but also underscores the system's commitment to optimizing efficiency and productivity. By seamlessly integrating human capabilities into the automated workflow, this solution harnesses the best of both worlds, ensuring robustness, reliability, and adaptability in a dynamic manufacturing environment.

The device manager acts as the central hub for communication, employing the MQTT protocol to interface with all device services outlined below. Tasked with overseeing the operational status of all devices, the administrator diligently monitors their conditions and initiates requests for new assignments from the Manufacturing Execution System (MES) for idle devices. Upon receiving new tasks from the MES, the administrator assesses the requirements and, if necessary, solicits additional data from the MES to facilitate the execution of the assigned jobs. Subsequently, the administrator assumes control over the equipment corresponding to the designated tasks, ensuring seamless coordination and operation. As devices complete their assigned tasks, they relay status updates to the administrator. In response to reports of task completion, the administrator promptly notifies the MES, providing essential feedback regarding the successful execution of the tasks associated with the respective devices. This bidirectional communication loop between the device manager and the MES optimizes workflow management and enhances overall system efficiency.

Error reports from devices are forwarded to MES where necessary decisions are made for further operations. According to the number of details needed to produce, MES can evaluate unused workstations and deciding 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 it to apply a similar method in the existing factory without making major adjustments for the robots. Each unit gives feedback about the current situation at the workplace to MES for the management of other units (Moor, Vaher, Riives, Kangru, & Otto, 2021).

3.3.3 Production plan

All production activities adhere meticulously to the predefined production plan, which dictates the allocation of resources for each operational task at any given moment. This dynamic production plan undergoes continuous recalibration, automatically adjusting following the completion of each operation or the introduction of a new order into the system. Additionally, for added flexibility, operators have the option to manually trigger a recalculation of the production plan by engaging the "Update" button located above the production plan interface.

To provide comprehensive visibility and facilitate efficient workflow management, all scheduled operations are presented in chronological order within the production schedule interface. Furthermore, a detailed list of planned operations accompanies the schedule, offering a comprehensive overview of upcoming tasks. As operations are initiated, the system records the start time in the "Reported start time" field, ensuring accurate tracking and documentation of workflow progression. This systematic approach to production planning and execution optimizes resource utilization and promotes operational transparency throughout the manufacturing process. The production plan is visualized on the user interface as given on figure 16.

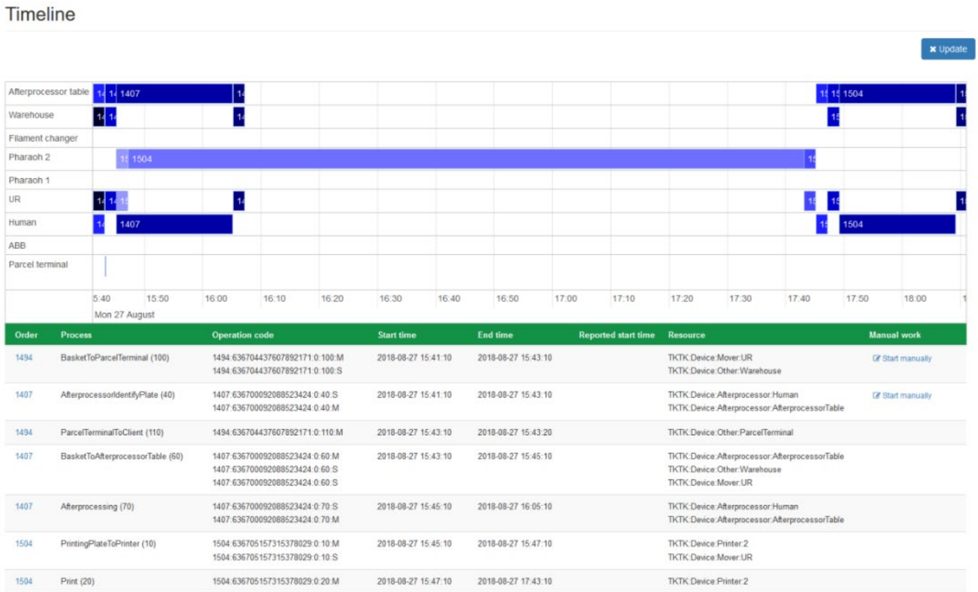


Figure 16. MES level HMI view of resource planning.

3.3.4 Control of the resources

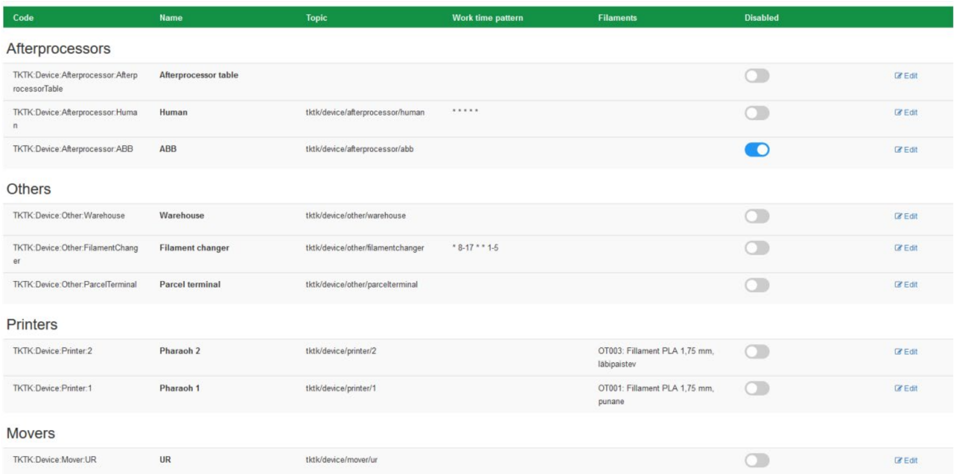
The device manager maintains seamless communication with all designated device services through the MQTT protocol, facilitating efficient data exchange and coordination. Meanwhile, the administrator assumes responsibility for monitoring the operational statuses of all devices within the system, actively managing their workflow and task assignments. Upon identifying available resources, the administrator initiates requests for new job assignments from the Manufacturing Execution System (MES), ensuring optimal utilization of available capacity. Upon receiving task details from the MES, the administrator evaluates the requirements and, if necessary, solicits additional data to support the execution of assigned tasks. Subsequently, the administrator assumes control over the relevant equipment corresponding to the designated tasks, overseeing their execution with precision and efficacy. Upon completion of tasks, devices report their status to the administrator, who promptly updates the MES regarding the successful completion of the associated work, maintaining real-time visibility and accountability throughout the operational cycle.

The main resources of the production line are:

- Collaboration robot UR (L01)
- Mobile robot MIR (L02)
- Collaboration robot ABB (L03)
- 3D printers (L04)
- Parcel terminal (L05)
- Automatic warehouse system (L06)
- Post-processing module (L07)

All laboratory resources are preconfigured and static, meaning they cannot be dynamically added or removed from the system. The "Code" attribute assigned to each resource serves as a unique identifier, ensuring consistent recognition and communication across the entire system, including interactions between devices. The "Topic" parameter designates the specific MQTT message to which the respective resource subscribes. This critical setting must be configured within the service settings of each individual resource, enabling seamless communication and data exchange within the system. By adhering to these standardized protocols, the system maintains robust interoperability and efficient resource management throughout its operations.

Within the resource management interface, as you can see on figure 17, operators have the capability to configure operation durations and work schedules. For printers specifically, additional parameters such as filament types currently installed can also be specified. Operational durations are expressed in seconds and exclusively utilized for production plan calculations, ensuring precise scheduling accuracy. Printers print times are automatically extracted from the .gcode file, streamlining the scheduling process. To define work schedules, a cron format is employed, allowing for flexible and customizable scheduling configurations tailored to specific operational needs. This comprehensive approach to resource management empowers operators to optimize scheduling efficiency while accommodating various operational requirements.



Code	Name	Topic	Work time pattern	Filaments	Disabled	
Afterprocessors						
TKTK:Device:Afterprocessor:AfterprocessorTable	Afterprocessor table					Edit
TKTK:Device:Afterprocessor:Human	Human	tktk/device/afterprocessor/human	* * * * *			Edit
TKTK:Device:Afterprocessor:ABB	ABB	tktk/device/afterprocessor/abb				Edit
Others						
TKTK:Device:Other:Warehouse	Warehouse	tktk/device/other/warehouse				Edit
TKTK:Device:Other:FilamentChanger	Filament changer	tktk/device/other/filamentchanger	* 8-17 * * 1-5			Edit
TKTK:Device:Other:ParcelTerminal	Parcel terminal	tktk/device/other/parcelterminal				Edit
Printers						
TKTK:Device:Printer:2	Pharaoh 2	tktk/device/printer/2		OT003: Fillament PLA 1,75 mm, läbipaistev		Edit
TKTK:Device:Printer:1	Pharaoh 1	tktk/device/printer/1		OT001: Fillament PLA 1,75 mm, punane		Edit
Movers						
TKTK:Device:Mover:UR	UR	tktk/device/mover/ur				Edit

Figure 17. List of resources.

3.3.5 Conclusion

Following successful tests and trial runs of the system, an evaluation was conducted to identify areas for improvement. The Internal Logistics module was one such area, which relied on a robot arm mounted on a mobile robot, as described in a previous study. However, this approach involved the use of two expensive resources, with one idle while the other was operational. To optimize resource utilization, a study was conducted to identify the most efficient means of integrating the robot arm with the production of parts in SME manufacturing companies. This involved assessing the use of machinery in the production process to determine the optimal means of linking the robot arm to the production line.

3.4 Simulation of the new approach

To demonstrate the efficacy of the proposed solution outlined in the thesis and its potential to improve production equipment efficiency within the industry, several simulations were conducted under diverse scenarios. Results confirm that the proposed approach can significantly increase equipment efficiency beyond the observed average of approximately 50% in most industrial companies studied (Vaher, Mahmood, Otto, & Riives, 2021). Simulations offer an efficient means of testing various production scenarios without the need for production interruption or rescheduling. They provide a quick and effective method of exploring different production scenarios and offer valuable insights for optimizing industrial production processes.

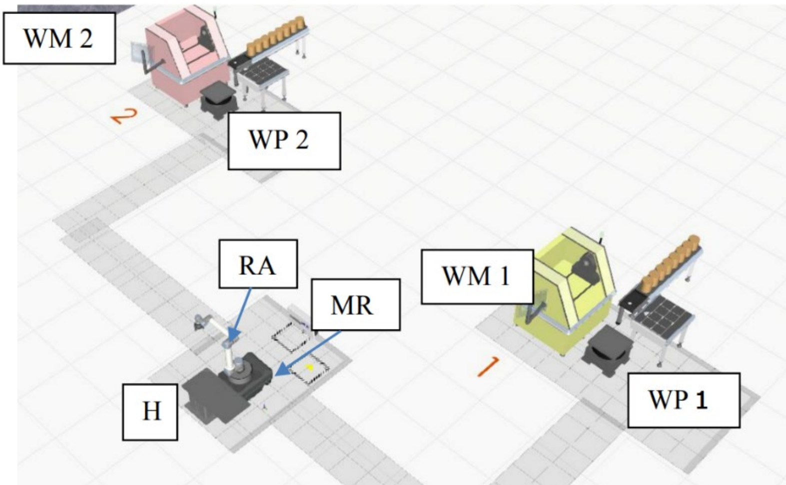


Figure 18. Robot arm (RA) moved by mobile robot (MR) between working positions (WP 1, WP 2), WM 1 and WM 2 are working machines, H is home position for mobile robot (Vaher, Mahmood, Otto, & Riives, 2021). ("Open Access proceedings Journal of Physics: Conference series - IOPscience")

In (Vaher, Mahmood, Otto, & Riives, 2021) research two different use cases were analysed. Use case A is a common way how a robot arm is used by SMEs. Use case B is a new method proposed by the author where the robot arm is moving constantly between WPs to execute tasks and reduce downtime.

Use case A

- Two workplaces, one robot arm, one mobile robot.
- Lot size 8 pieces (parts that are produced with machines, see Table 1)
- Operation time for WM1 is 3 minutes per part and for WM2 is 5 minutes per part.
- All parts are produced first in WM1 and then goes to WM2. Robot stays with WM1 until parts are ready and then moves to WM2 and stays there until all parts are done. ("Open Access proceedings Journal of Physics: Conference series - IOPscience")

Use case B

- Two workplaces, one robot arm, one mobile robot.
- Lot size 8 pieces (parts that are produced with machines)
- Operation time for WM1 is 3 minutes per part and for WM2 is 5 minutes per part.

- WM1 and WM2 are working at the same time. Robot arm is moving constantly between WM1 and WM2.
- "The Mobile robot leaves after it has moved the robot arm." ("Simulation based feasibility analysis of autonomously movable robot arm")

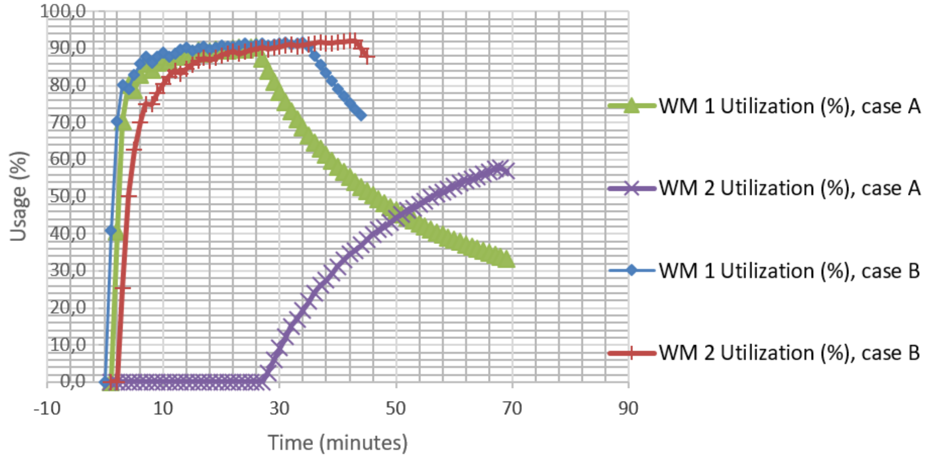


Figure 19. Working machine's (WM) utilization and working time. (Vaher, Mahmood, Otto, & Riives, 2021)

Comparing the WM 1 and WM 2 utilization of use case A and B, it can be seen on figure 19 that the utilization of use case A is very low but for use case B it is very high, close to 90%. ("Open Access proceedings Journal of Physics: Conference series - IOPscience") At the same time, a large decrease in production time can be seen. "Production time for user case A is 68 minutes and for use case B it is 44 minutes, i.e. the production time is reduced by approx. 35%." ("Open Access proceedings Journal of Physics: Conference series - IOPscience")

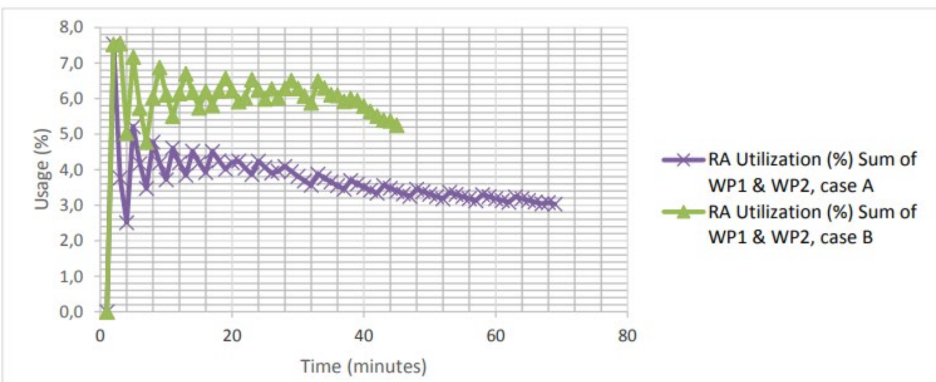


Figure 20. Robot arm (RA) utilization in use case A and B. (Vaher, Mahmood, Otto, & Riives, 2021)

Robot Arm Utilization time is given as sum of both working positions (WP 1 and WP 2). For use case A utilization is low, 3,7 %. This is because the RA does not work during the working hours of the WM. In use case B the RA is moved between two WP constantly and utilization of RA is increasing almost 2 times, as shown on figure 20, and total working hours are reduced from 63 minutes to 43 minutes.

Moving the robotic arm between working positions can significantly increase WM utilisation and robot arm usability.

3.5 Building a test machine

To prove the theoretical method presented in the previous study in practice, the author wanted to build a test device that would be able to check the performance of the theory in the working environment.

The construction of the machine, shown on figure 18, was based on the availability of industrial components available on the market, so that the construction of the machine would be cheap and its construction repeatable. Main components that the author chose were:

- Mobile industrial robot (MIR 100),
- Cobot (UR 10),
- Machine vision camera (Cognex IS2000M).

The self-developed part of the machine was the frame together with the batteries and it’s charging solution since no suitable ready-made product was found on the market.

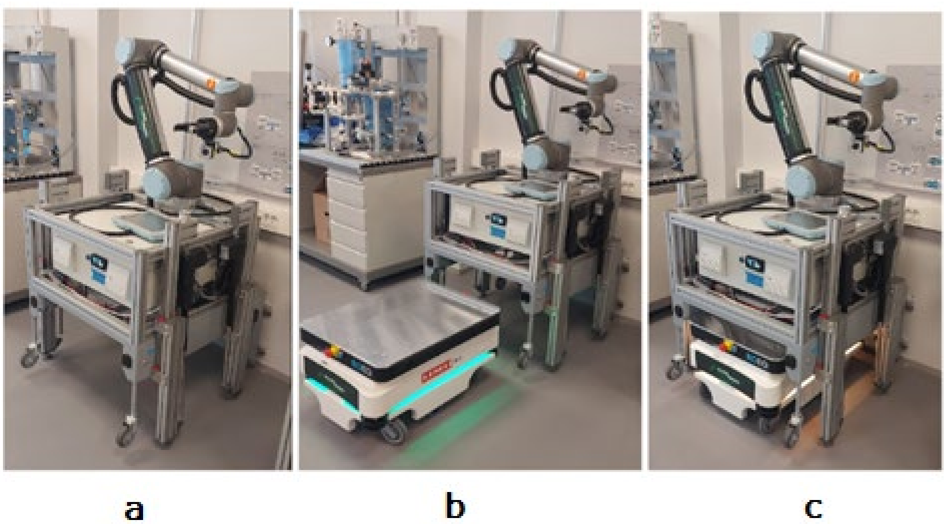


Figure 21. Autonomous transportation solution for robot arm. Frame in working position (a), mobile robot is picking up the frame (b), robot arm is ready for transportation (c).

Constructed solution can work independently, but its work is constrained by low accuracy. The main problem is the different accuracy of the two machines. The robot arm can reposition itself within ± 0.05 mm (universal-robots.com, 2022). The positioning accuracy of the mobile robot is ± 10.0 mm if it is using a positioning marker. Without it, the accuracy is even worse, ± 50.0 mm (mir.com, 2022). Due to the low accuracy of the mobile robot, its positioning error is transmitted to the work of the robot arm and the accuracy of the robot arm will be ± 10.0 mm. This big difference causes a problem for the robot arm. The robot job is to pinpoint certain objects where the accuracy must at least ± 1 mm or even better.

The positioning accuracy of the mobile robot cannot be improved to the level of robot arm. The solution should come from an external device or sensors. The solution is to use machine vision to detect markers and evaluate offset from zero condition. The use of machine vision in this application is described in more detail in an article (Vaher & Otto, 2020).

The camera what was used in the experiment was Cognex IS2000M-130-40-00 with 25 mm lens. The communication with robot is done with the RPC server, which in turn communicates with the camera via telnet as shown on figure 21.

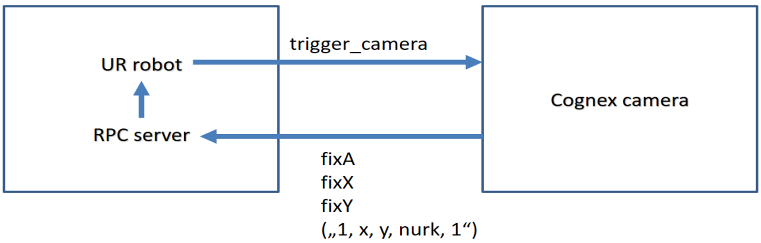


Figure 22. Communication between camera and RPC server.

The RPC server is configured to port 555 and has 3 features:

- start_camera_telnet: This function must be executed in the UR in any program that requires communication with the camera. The function expects no values and returns either 0 (communication with the camera failed) or 1 (communication with the camera succeeded).
- change_camera_job: Function can be used to change the camera job if needed. It waits for one value (the job number) and returns one of three options - 0 (camera job exchange failed), 1 (camera job exchange succeed), or 2 (the camera already had the job loaded and nothing was changed).
- trigger_camera: The function can send a capture command and does not expect any value. FUNCTION returns one of three options, "0,0,0" (failed to send command to camera), "1,0,0,0,0" (failed to send command to camera, but the camera job did not finish successfully), or "1, x, y, angle, 1 "(command was successfully transmitted to the camera, coordinates of the detected object and camera job succeeded). Given x and y are relative to the camera.

There are three sub-programs for UR for using the camera:

- Camera_Start: this program needs to be run before using other camera functions
- Camera_Trigger: The program sends a camera capture command and receives new X, Y and angles in response
- Camera_Change_job: Changes the camera job. Variable jobID: must be the number of the corresponding job

Machine vision significantly improved the accuracy of the robot arm due to inadequate positioning accuracy of the mobile robot. ("Positioning Error Correction of Autonomusly Movable Robot Arm") With machine vision a repositioning accuracy of +/- 0.5 mm for the robot arm was achieved. The robot arm itself has an accuracy of 0.05 mm, but the result of machine vision is sufficient to perform most of the tasks.

3.5.1 Energy solution

The energy solution and distribution, as depicted in figure 23, is designed to provide uninterrupted power supply to the robot, irrespective of its charging status or battery operation. Automatic charging is initiated by connecting the charger to the mains, with charging operations regulated by the Battery Management System (BMS). The UR robot receives charging-related data and needs from the BMS, enabling autonomous decisions on charging requirements and timing. Charging is facilitated at the designated workstation where the charging option is incorporated, wherein the robot autonomously connects and disconnects the plug from the power grid, rendering the entire process fully automated without human intervention. Consequently, this solution enables continuous and uninterrupted operation.

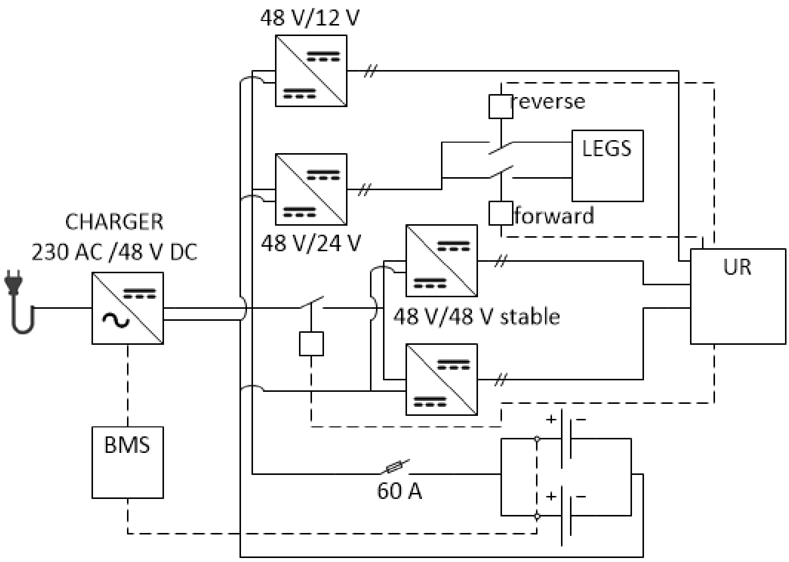


Figure 23. Uninterrupted power solution and energy distribution.

3.5.2 M2M communication

The communication between the machines is structured in a way where the machines are given the command to run the program and wait for feedback about the success or failure of the program execution. Through the central server, the operation of the machine itself is not controlled. All the programs of all machines for all operations are previously stored in the machines. Software on MES level is calling those programs. Principle of the system communication is also discussed in the author 's article (Vaher, Vainola, Otto, & Riives, 2019). The machines that are part of the system can not always be connected to the existing WiFi network of the factory level, because they are often closed systems and new arrivals are not very welcome. For this purpose, this system was created with its own Wi-Fi 2.4 GHz communication network. The principal scheme is shown in figure 24. In this way, setting up the system does not depend on the network or lack of it at the factory side. WiFi network is needed because some devices are mobile and therefore cannot relate to a cable. The coverage range of the Wi-Fi network with one antenna is not very large, but it can be increased to the entire production area by adding additional antennas.

The task of the robot arm is to service various working machines (WM) on production level such as a lathe, CNC machine tool, etc. at the production level. Many such devices, especially those of the older generation, are not ready to communicate over a Wi-Fi network. If the WM could issue and receive signals related to the control of its work (door opening, package opening, start signal, end of work signal), then an additional minicomputer (Raspberry Bi, Arduino, etc.) can be used for this purpose, which creates a WiFi connection to connect the WM to it. Mini PC relates to WM with analogue and I/O signals.

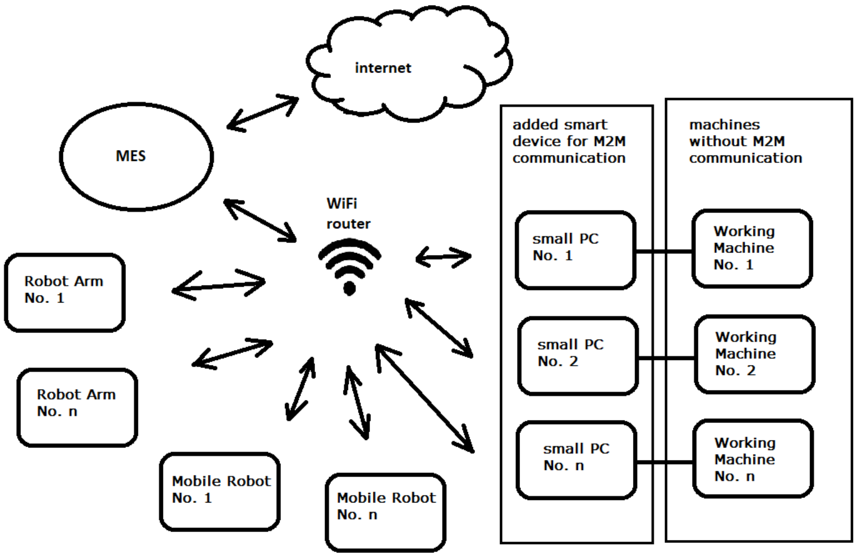


Figure 24. Principle of communication between different machines.

3.6 Positioning accuracy test

The camera that was used in the experiment was Cognex IS2000M-130-40-00 with 25 mm lens. The camera has monochrome image recognition. The focal length is manually adjustable, which meant that the same marker was detected exactly at the same distance for all the detection points. In this project, the detection distance was set at 300 mm.

Next to each working position, an L-shape sticker, as shown on figure 25, was added, rigidly connected to working stations such as the 3D printer or the parcel cabinet (Vaher, Vainola, Otto, & Riives, 2019). L-sticker was used to define the position of the mobile robot in relation to the working station. Each time the mobile robot entered a working position, the L-sticker was captured with camera and the offset from zero position was calculated and added to the program of the robot arm.

A new program for a new location could be programmed with the UR control panel. The *Camera Start* subroutine had to be chosen at the beginning of the UR program. The camera that has a manually adjustable focal point had to be positioned over a subject (300 mm). (“Journal of Machine Engineering, 2020 Vol. 20 No. 4 152 160”) Stop command had to be selected at this point. "After that, the camera trigger subroutine had to be called." (“Positioning Error Correction of Autonomusly Movable Robot Arm”) After triggering the camera, three variables (fixX, fixY and fixA) occurred, these variables had to be noted.

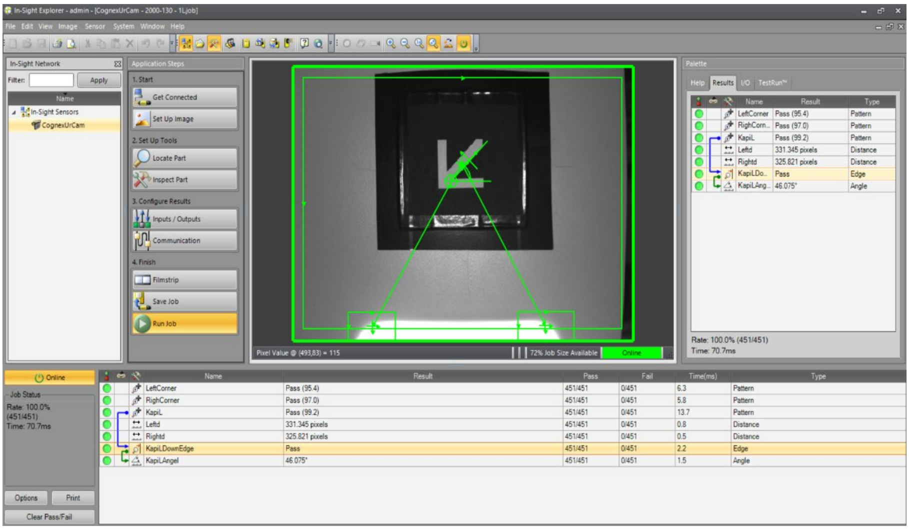


Figure 25. Settings for L-sticker deduction with camera (software In-Sight Explorer).

For machine vision test, the following mathematical approach was given to the UR program to consider with data coming from Cognex camera:

Robot arm base coordinates

$$Base_{var} \coloneqq p[0{,}0{,}0{,}0{,}0, nurk] \tag{1}$$

Where angle correction formula is:

$$nurk \coloneqq (firstA - fixA) * -1 \tag{2}$$

Where,

firstA is known angle for UR 10 robot arm

fixA is new angle given by camera

Coordinates X and Y correction formulas are:

$$addX \coloneqq \frac{firstX - fixX}{1000} \tag{3}$$

$$addY \coloneqq \frac{firstY - fixY}{1000} \tag{4}$$

Where,

firstX and firstY are known coordinates for UR 10 robot arm

fixX and fixY are new coordinates given by camera

New robot arm base coordinate is calculated according to the information from machine vision and with this formula:

$$pose\_add(Base_{var}, p[addX, addY, 0{,}0{,}0{,}0]) \tag{5}$$

3.6.1 Repeatability tests

A total of 50 experimental trials were conducted for each test. Three different tests were carried out. The experimental setup involved a predefined procedure wherein the mobile robot navigated to its designated position, robot arm executed a specific movement, mobile robot exited the position, performed a slight rotation, and subsequently returned to the initial position for the repetition of the robot arm's movement. This sequence was repeated 50 times, ensuring enough iterations for accurate assessment and analysis. Three different tests were carried out where two test had different methods for mobile robot positioning (Test #1 and Test #2) and two test had same method for positioning but different method for robot arm positioning (Test #2 and Test #3).

Three different tests were carried out in testbed with the layout shown in the figure 26:

Test # 1 - positioning without positioning marker
Test # 2 - positioning with VL-marker
Test # 3 - positioning with VL-marker and machine vision

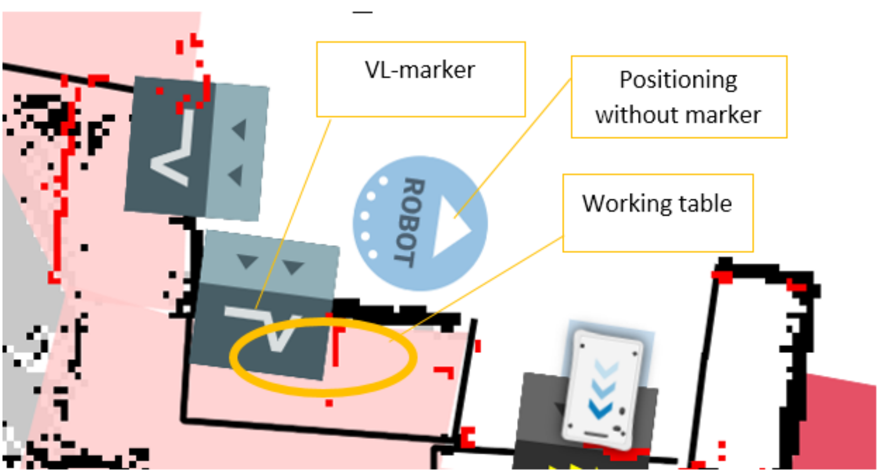


Figure 26. A laser scanned map of the mobile robot with positioning locations.

The results of Test #1 shown on figure 27, that by positioning freely on the map without a marker, the mobile robot can reposition itself in X-axis +/-50 mm and in Y-axis +/-45 mm.

The results of the Test #2, shown on figure 27, that by using the VL- marker, the robot can reposition itself on the X-axis with an accuracy of +/-5 mm and on the Y-axis with an accuracy of +/-3.5 mm.

The results of the Test #3, shown on figure 27, that by using machine vision, the robot arm can reposition itself on X-axis direction with an accuracy of +/-0.5 mm and on the Y axis with an accuracy of +/-0.7 mm.

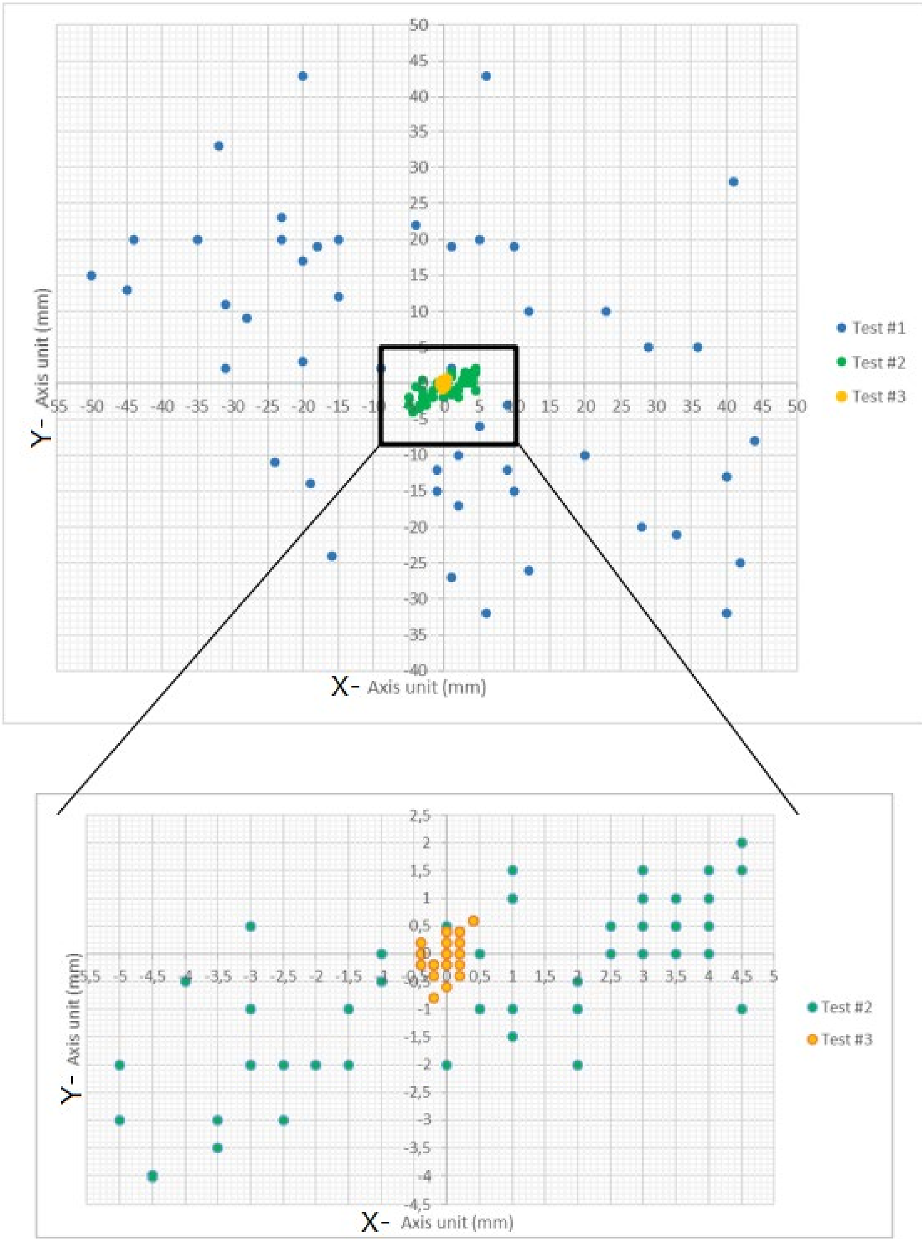


Figure 27. Results of the three different tests.

Standard deviation is utilized in evaluating the repositioning accuracy of a robot arm through the assessment of variability or dispersion within the arm's positioning data. To evaluate repositioning accuracy using standard deviation (Eq. (6)), multiple measurements of the robot arm's position are taken during its task execution. By computing the standard deviation of these position measurements, the consistency and precision of the robot arm's repositioning capabilities can be determined. Utilizing standard deviation as a metric enables a quantitative evaluation of the repositioning accuracy of the robot arm, facilitating performance assessment, identification of inconsistencies or deviations, and the implementation of necessary adjustments or enhancements to improve precision and reliability.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{6}$$

Where,

n is number of data points,
$\bar{x}$ is mean (average) of the data set and
x_i is each individual data point.

The experimental procedure yielded values for the x and y axes with respect to the reference point, which is defined as the origin (0, 0). In the context of robot positioning evaluation, the assessment of positional accuracy is currently focused on measuring the deviation of the robot's position relative to this reference point. To quantify this deviation, the Euclidean distance between each data point and the origin was calculated using their respective coordinates.

$$x_i = R_i \tag{7}$$

Where,

x_i is each individual data point,
R_i is data point distance from the scale centre.

Table 1. Results for three different tests.

	R_{max}	R_{AVR}	σ
Test #1	61,87 mm	37,28 mm	12,33 mm
Test #2	6,08 mm	3,84 mm	1,03 mm
Test #3	0,71 mm	0,42 mm	0,15 mm

In statistics, the empirical rule (also known as the 68-95-99.7 rule) states that for a normal distribution (bell-shaped curve), approximately 68% of the data falls within one standard deviation of the mean, about 95% falls within two standard deviations, and roughly 99.7% falls within three standard deviations. This empirical rule can be used to make general statements about the likelihood of data points falling within a certain range based on the standard deviation. However, it's important to note that the empirical rule assumes a normal distribution, and the actual distribution of data may vary. The specific probability associated with a given standard deviation would depend on the characteristics of the dataset and its underlying distribution.

To achieve approximately 95% confidence that a measurement will lie within the upper and lower limits, two standard deviations can be employed with equation 8. In a normal distribution, about 95% of the data points are anticipated to reside within two standard deviations of the mean. By computing the upper and lower limits utilizing two standard deviations from the mean, a range can be established wherein there is a reasonable level of confidence that measurements will fall. This range grants a degree of certainty regarding the dispersion of the data and aids in evaluating the probability of observing measurements outside of this range.

The formula for calculating two standard deviations from the mean:

$$Max = \overline{X} + (2 * \sigma)$$
$$Min = \overline{X} - (2 * \sigma) \quad (8)$$

Where,

$\overline{X}$ is means,

σ is standard deviations

Table 2. Results of two standard deviations calculation.

	Upper Limits	Lower Limits
Test #1	62,26 mm	12,30 mm
Test #2	6,74 mm	0,94 mm
Test #3	0,73 mm	0,11 mm

3.7 Conclusion of the test and machine building

Integrating a Cognex camera with the Universal Robots robot arm presents a technically straightforward process that requires minimal programming effort. Despite the inapplicability of the Cognex application for the UR robot interface, effective collaboration between Cognex and UR has been achieved. This challenge was addressed by utilizing server scripts written for the UR robot controller, which were triggered within the UR program as required.

The implementation of machine vision has played a significant role in improving the precision of the robot arm, particularly considering the suboptimal positioning accuracy of the mobile robot. Through the utilization of machine vision, a remarkable repeat accuracy of +/-0.5 mm for the robot arm was attained. While the inherent accuracy of the robot arm itself is +/-0.05 mm, leveraging machine vision yielded satisfactory results for most tasks. It is worth noting that employing higher-quality and more advanced cameras can lead to even more precise outcomes.

Mathematical analysis indicates that a standard deviation of 0.15 mm can be achieved (Test #3), further underscoring the potential for improved accuracy through the application of machine vision technology.

Consequently, a solution has been developed whereby the robot arm is transported between various working positions using a mobile robot. This innovative approach allows for a substantial increase in the robot arm's working hours without necessitating extensive reorganization of existing factory setups. Additionally, the utilization of WM has been maximized to a significant extent.

By employing a mobile robot, the need for a dedicated individual responsible for moving the robot arm between different workstations is eliminated. Furthermore, the charging of such a solution can be autonomously handled by the machine itself. The integration of a robotic arm onto a mobile robot empowers continuous operation, enabling round-the-clock utilization, while also offering greater flexibility in reconfiguring production processes compared to static robot arm installations.

During the testing phase, challenges were encountered in accurately positioning the mobile robot in relation to the marker. This difficulty arose from the fact that the frame being carried by the mobile robot exceeded its optimal weight capacity, resulting in issues with the drive wheels slipping. The mobile robot relies on both internal (wheel encoder) and external (LIDAR) information for positioning using the simultaneous localization and mapping (SLAM) method. Due to the slipping wheels, the accuracy of the positioning information derived from one data source was compromised, leading to inaccuracies in aligning the mobile robot with the marker. Regrettably, the MIR 100 mobile robot lacks the capability to disable the internal information specifically for positioning purposes. However, this problem was mitigated during subsequent movements when the mobile robot entered the marker area. In these instances, the overlapping internal and external information was corrected while the robot was in transit, ensuring more accurate positioning.

3.8 Transport system for autonomously moving between different working locations and precisely positioning of the collaborative robot at different working stations

The present chapter is based on an original Estonian patent application entitled "*Transpordisüsteem koostööroboti autonoomseks teisaldamiseks eri tööpositsioonidele ja täpseks positsioneerimiseks eri tööjaamadel*" ("Transport system for autonomously moving between different working locations and precisely positioning of the collaborative robot at different working stations").

The application, filed on 30 September 2024 with the Estonian Patent Office, serves as a primary-source record of the invention and substantiates its novelty and practical relevance within this doctoral study. The purpose of including this patent application is to provide primary source evidence of the original invention and demonstrate the novelty and practical applicability of the robotic positioning system developed during this doctoral research. In Estonia, patent applications can be treated as equivalent to scientific publications, primarily within the framework established by the Estonian Research Information System (ETIS) and the evaluation guidelines provided by the Estonian Research Council (ETAg).

This invention proposes a modular transport system designed to autonomously move and accurately position collaborative robots (cobots) at various workstations within a manufacturing or industrial setting. The primary aim is to enhance production flexibility by allowing cobots to be easily relocated without human intervention, while ensuring precise alignment for immediate task execution.

The key novelty lies in the independent modular architecture: three modules - the autonomous transport robot, transport frame, and collaborative robot - operate independently yet in cooperation. This architecture enables concurrent tasks—for example, while the cobot is working, the transport robot can perform other logistics operations.

Technically, the system includes a machine vision-guided positioning system, allowing the cobot to align with an accuracy of ±0.01–0.05 mm. The transport frame features wheeled support posts for mobility and telescopic legs for stable positioning during work. An energy management system with battery, charging interface, and robot-controlled plug connection ensures uninterrupted power. All components communicate via a wireless (e.g., WiFi) network, managed by MES software that handles coordination, scheduling, and integration with factory systems. The decoupling of mobility, fixturing, and manipulation elevates overall-equipment effectiveness by eliminating non-productive waiting states, enables near-instant cell reconfiguration through software scheduling alone, and establishes a scalable pathway toward plug-and-play “robot-as-a-service” deployments inside high-mix, low-volume factories.

This novel solution is especially relevant for doctoral research in smart manufacturing, robotics, and Industry 4.0, offering a practical example of autonomous robotic mobility, precise vision-based positioning, and distributed communication systems. It reflects current trends toward flexible, modular automation and supports scalable multi-robot cooperation in dynamic industrial environments.

The full original text follows in Annexe to ensure transparency and accuracy of technical details as officially submitted to the Estonian Patent Office.

4 Conclusion

Integrating different technologies to achieve better and more effective solutions is not only feasible but also quite common in many industries. In fact, many advanced systems and processes are a combination of various technologies working together seamlessly. The key to successful integration is careful planning and coordination between the different technologies involved. Each technology needs to be properly configured and integrated with the others to ensure smooth communication and efficient operation. This often involves the use of standard communication protocols and interfaces, as well as custom software and hardware integration. The integration of different technologies is a critical aspect of modern industrial automation and can lead to significant improvements in productivity, quality, and safety.

According to surveys and research, the implementation of industrial robots among small and medium-sized enterprises (SMEs) has not been as successful as in larger industrial companies. One reason for this is that stationary robots may not have enough work assignments without a major production reorganization. However, companies are interested in utilizing robots more extensively.

To address this issue, a proposed solution involves using a mobile robot to transport the robot arm between different working positions. This approach allows for a high level of utilization for the robotic arm without the need for a major reorganization of the existing factory. The objective of the research was to develop new approaches for utilizing both mobile robots and robot arms.

Simulations are powerful tools for analysing flexible production solutions that involve random changes. These simulations allow for the determination of production time, identification of bottlenecks, and identification of necessary changes to ensure smooth production, and estimation of the required number of robots. Compared to mathematical models, simulations are easier and more cost-effective to set up, resulting in reduced planning time for factories. Simulation is a critical component of digital manufacturing and Industry 4.0, and its use is expected to continue to grow. As industries move towards Human Robot Collaboration, simulations can ensure the safety of human operators and optimize task allocation between robots and operators. When building and validating robotic cell simulation models, physics engines are crucial criteria to consider. Thus, physics engines should be considered an essential aspect when building a digital twin model of a robotic process.

To address the issue of inadequate positioning accuracy of mobile robots, machine vision has significantly improved the accuracy of robot arms. With machine vision several tests were conducted and a repeat accuracy of +/- 0.5 mm for the robot arm was achieved, and even better accuracy can be attained with higher-quality cameras. While the robot arm itself has an accuracy of 0.05 mm, the results of machine vision are sufficient to perform most of the tasks that robot arm can to in industrial companies.

The research questions that were raised at the beginning of the work were answered as follows:

RQ1: How can small and medium-sized enterprises (SMEs) be enabled to utilize robots more effectively in situations where there is not enough workload to justify the installation of a robot at a single location?

Answer: The study provided a comprehensive examination of the utilization and transportation of a robot arm within a shop floor context. Consequently, a proposed solution emerged, wherein the robot arm is dynamically relocated between distinct workstations with the assistance of a mobile robot. This approach facilitates a substantial increase in the robot arm's active working hours, obviating the necessity for extensive factory reorganization. The utilization of a mobile robot eliminates the requirement for human intervention in transporting the robot arm between workstations, enabling continuous operations, and offering enhanced production reconfiguration flexibility compared to a stationary robot arm setup.

RQ2: What combination of technologies can be used to enable industrial robots to operate autonomously and achieve sufficient precision for servicing industrial equipment (e.g., latches, CNC machines, etc.) while also being mobile?

Answer: To enable industrial robots to achieve autonomous operation and sufficient precision while maintaining mobility for servicing industrial equipment, the author undertook a practical approach. A test device was constructed (depicted in Figure 20) utilizing available industrial components to ensure cost-effectiveness and reproducibility. The key components selected for this configuration included a Mobile Industrial Robot (MIR 100), a Collaborative Robot (Cobot UR 10), and a Machine Vision Camera (Cognex IS2000M). To address the unique requirements of the project, a self-developed frame integrated with batteries and a charging solution was designed, as no suitable off-the-shelf product was identified in the market. Through this combination of technologies and a purpose-built machine, the theoretical method was substantiated by evaluating its performance in a real-world working environment.

RQ3: How to evaluate the need of a flexible robot solution or robots in quantity based on the information of production batch and parts per batch?

Answer: Simulation tools are invaluable assets in the realm of intelligent manufacturing, particularly when evaluating the need for flexible robot solutions or determining the required quantity of robots based on production batch and parts per batch information. By leveraging digital twins and virtual environments, manufacturers can efficiently test various scenarios, optimize production processes, and reduce the risk of costly errors before implementing physical changes on the production line. The integration of industrial robots into simulation tools empowers manufacturers to assess different production scenarios, improve efficiency, safety, and quality, and optimize the implementation of robotic systems in factory settings. Ultimately, the utilization of simulation tools enables a more efficient and informed approach to intelligent manufacturing.

5 Future work

The practical validation of the concept has been accomplished, and the objective is to persist in the development efforts towards creating an improved machine that better suits the industrial environment. The primary objective is to enhance the test machine using the latest and most advanced components and to execute assessments in an authentic working setting. The technological proficiency of the camera utilized has evolved considerably with time, and currently, a camera with much-improved image quality and more precise positioning, within the same cost bracket, can be used.

The aim in the near future is to design an innovative solution for the autonomous mobility of bigger "cage robots." These robots have higher safety requirements, and they must be considered in the new solution.

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Abstract

Reconfigurable Manufacturing Based on Autonomously Movable Industrial Robot Solutions

Manufacturing has been revolutionized with the adoption of industrial robots. Today, industrial robots are widely used in various industries to perform tasks such as material handling, welding, painting, assembly, and inspection. The use of industrial robots has resulted in increased efficiency, improved quality, and reduced labour costs for manufacturers.

Reconfigurable manufacturing systems (RMS) have emerged as a promising solution to address the challenges posed by today's dynamic market demands. RMS can provide greater flexibility and responsiveness to adapt to rapidly changing production requirements, allowing for increased productivity and reduced costs. Autonomously movable industrial robot arms have been identified as a key enabling technology for RMS. By integrating these robot arms into manufacturing processes, companies can enhance their production efficiency, reduce lead times, and increase their ability to adapt to changing market demands.

These systems can be designed to be modular and reconfigurable, allowing for easy adaptation to changing production needs. This is particularly important for small and medium-sized enterprises (SMEs), which often face resource constraints and need to be able to quickly adjust their production processes to meet changing market demands.

The use of autonomously movable industrial robot arms in RMS allows for greater automation and efficiency, reducing the need for manual labour and increasing production output. The robot arms can be programmed to perform a variety of tasks, such as material handling, assembly, and quality control, and can move autonomously within the manufacturing facility.

One of the key advantages of the autonomously movable industrial robot arm systems is their ability to operate independently and without the need for human intervention. This reduces the risk of errors and increases the reliability and consistency of the manufacturing process. Moreover, the robot arm systems can work in collaboration with human operators, thereby enhancing the overall productivity and efficiency of the manufacturing process. Furthermore, the integration of sensor technologies, such as machine vision and force sensing, can enable the robot arms to perform more complex tasks, such as object recognition and manipulation, leading to further efficiency gains.

In summary, the adoption of reconfigurable manufacturing systems based on autonomously movable industrial robot arms has the potential to significantly improve the competitiveness of SMEs by providing greater flexibility, responsiveness, and efficiency in their manufacturing processes.

The integration of the robot with the existing system can highlight a problem where it turns out that there is not enough work for the robot in one specific position. The reasons behind underutilization of robots in manufacturing, including the lack of work for robots in a single position. Underutilization of industrial robots in SMEs need to improve robot flexibility and adaptability for to different tasks.

The objective of this study is to investigate the underlying causes of the limited adoption of industrial robots within small and medium-sized enterprises (SMEs), and to devise a novel approach for enhancing the efficient utilization of industrial robots in this sector.

Lühikokkuvõte
Autonoomselt teisaldataval tööstusroboti lahendusel põhinev ümberseadistatav tootmine

Erinevate tehnoloogiate integreerimine paremate ja tõhusamate lahenduste saavutamiseks on mitmes tööstusharus mitte ainult teostatav, vaid ka üsna tavaline. Tegelikult on paljud arenenud süsteemid ja protsessid erinevate tehnoloogiate sujuva koostöö kombinatsioonid. Eduka integreerimise võti on hoolikas planeerimine ja koordineerimine erinevate tehnoloogiate vahel. Iga tehnoloogia tuleb korralikult konfigureerida ja integreerida teistega sujuva suhtluse ja tõhusa toimimise tagamiseks. Selleks on sageli vaja kasutada standardseid suhtlusprotokolle ja liideseid, samuti kohandatud tarkvara- ja riistvaraintegratsiooni. Erinevate tehnoloogiate integreerimine on kaasaegse tööstusautomaatika oluline aspekt ja võib viia olulistele edusammudele tootlikkuse, kvaliteedi ja ohutuse valdkonnas.

Uuringud ja teadustööd on näidanud, et tööstuslike robotite rakendamine väike- ja keskmise suurusega ettevõtetes pole olnud nii edukas kui suuremates tööstusettevõtetes. Üheks põhjuseks on see, et statsionaarsetel robotitel võib puududa piisavalt tööülesandeid suuremahulise tootmisreorganiseerimise vältimiseks. Selle probleemi lahendamiseks on välja pakutud lahendus, kus mobiilne robot transpordib tööstusrobotit erinevate töökohtade vahel. See lähenemine võimaldab roboti kõrget kasutusastet olemasoleva tehase suuremahulise reorganiseerimise vajaduseta. Uurimuse eesmärk oli välja töötada uusi lähenemisviise nii mobiilsete robotite kui ka robotkäte kasutamiseks.

Simulatsioonid on võimsad tööriistad juhuslikke muudatusi sisaldavate paindlike tootmislahenduste analüüsimiseks. Need simulatsioonid võimaldavad määrata tootmisaega, tuvastada kitsaskohti ja teha kindlaks vajalikud muudatused sujuva tootmise tagamiseks ning hinnata vajalikku robotite arvu. Võrreldes matemaatiliste mudelitega on simulatsioone lihtsam ja kulutõhusam seadistada, mille tulemusena väheneb tehaste planeerimisaeg. Simulatsioon on digitaalse tootmise ja tööstus 4.0 kriitiline komponent ning selle kasutus kasvab eeldatavasti jätkuvalt. Kuna tööstused liiguvad inimene-robot koostöö (HRC) poole, võivad simulatsioonid tagada ohutuse ja optimeerida ülesannete jaotust robotite ja operaatorite vahel. Robotrakkude simulatsioonimudelite ehitamisel ja valideerimisel on füüsikalised mootorid olulised kriteeriumid, mida tuleb arvestada.

Mobiilsete robotite ebapiisava positsioneerimistäpsuse probleemi lahendamiseks on masinnägemisel suur tähtsus mille tulemusel on võimalik mobiilse roboti suurt ebatäpsust vältida. Masinnägemisega viidi läbi mitmeid katseid ja saavutati robotkäe kordustäpsus +/- 0,5 mm ning veelgi paremat täpsust on võimalik saavutada kvaliteetsemate kaameratega. Kui robotkäe enda täpsus on 0,05 mm, siis masinnägemise tulemused on piisavad enamiku tööülesannete täitmiseks, mida robotkäsi tööstusettevõtetes suudab.

Antud töö tulemusena töötati välja uus viis kuidas tööstusroboteid saab oluliselt efektiivsemalt kasutada olukordades kus robotile pole ühes kindlas töökohas piisavalt tööd. Välja töötatud lahendusega saab tööstusroboteid tootmises ringi liigutada ilma, et selle tarvis kahte kallist ressurssi (robotkäpp ja mobiilne robot) peaks omavahel jäädavalt siduma.

Appendix

Publication I
Vaher, K.; Vainola, V.; Otto, T. (2019). Industry 4.0 Laboratory. IV International Scientific Conference, Industry 4.0. Summer session, 52–53. volume 1/5 06.2019, Burgas, Bulgaria.

INDUSTRY 4.0

INTERNATIONAL SCIENTIFIC CONFERENCE SUMMER SESSION “INDUSTRY 4.0, 24-27 JUNE 2019, BURGAS, BULGARIA

INDUSTRY 4.0 LABORATORY

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1. Introduction

As the deployment of robots is a reality today and at an increasing pace, there is a growing need for people who can handle robots and other new technologies. The use of robots in industry is largely influenced by the lack of qualified labor. There is a need for people who can install, set up, maintain, program robots, set up data networks and more. At the same time, business leaders must educate themselves about robots so they can better understand how robots affect the "big picture" of production [2,3].

In order for robots to be better implemented, people need to be educated and there is a big part to do for the education system. Robotics includes knowledge in a wide variety of fields - physics, electricity, automation, mechanics, IT. You also need to know the specifics of the robot's field of application. All this has to be taught in a standard volume curriculum [2].

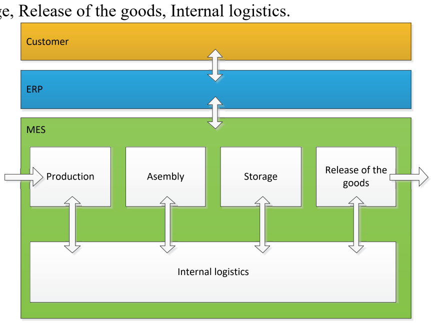
The goal is to create a learning laboratory where can be demonstrated a comprehensive automated process from order in the ERP system to the completion and storage of the final product. The purpose of building a system is to deploy as much as possible the topics discussed in the Industry 4.0 concept, such as robots, 3D printing, Radio frequency identification (RFID), Enterprise resource planning (ERP), Manufacturing execution systems (MES) etc.

2. Solution of the examined problem

When creating the concept, the author put himself in the position of the entrepreneur where he have to chose the equipment from the market that is compatible and capable to communicate with existing devices at shop floor. When building the system, the equipment was chosen from among the most used in the industry and among those that are able to communicate with third-party software solutions.

The design of the system's logic was based on the fact that the failure of one device or the occurrence of an error would not affect the operation of other devices, as long as other devices have tasks to do. The factory works 24/7 and is 100% automated, but that does not mean that a person is excluded from the system. In this solution, a person can perform many of the same tasks that robots do. Starting and completing a task must be confirmed on the MES-related user interface.

The system is divided into five major modules: Production, Assembly, Storage, Release of the goods, Internal logistics.



Each module contains one or more devices. Top of the modules is MES (Manufacturing execution systems), which coordinates the work of all modules and their communication. Each module is a stand-alone unit that works independently of other modules. The connection between the modules is only through the movement of the produced product it self.

Resource management is done by ERP. Its function is to make production plane based on customer orders and consequently the need for materials and supplies. Production is not directly controlled by the ERP system, due to the fact that it is not possible to precisely define all the processes in time. System management remains at the level of the MES program.

One of the important modules of the system is a **Internal logistics** where are used devices like mobile robot and robot hand. Robot arm is installed top of mobile robot. The purpose of this module is to serve all other modules by providing the necessary components and transporting the finished product between different modules. The mobile robot is freely orientated in the room based on a previously scanned map. The robot can stay in the room with the person, because the robot uses LIDAR's to avoid collision with obstacles. When the mobile robot moves, the robot arm is in driving position. It works only if mobile robot have stop.

The design of the MES system was based on the need for the system to be modified later and for the system to be able to add new modules and devices such as a quality control module or CNC bench to the production module.

3. Results

The study lab was prepared at TTK University of Applied Sciences (Tallinn, Estonia). With the completed laboratory, the university can demonstrate to students and use the full functionality and essential parts of a 100% automated production system. Students will get hands-on experience and are more aware of the possibilities of implementation new technologies and interconnecting them. Students will have much better practical knowledge's when entering the labor market. Industry 4.0 study labs gives knowledge about robots, mobile robots, 3D printers, RFID technology, MES and ERP programs, and their collaboration with each other.

The learning laboratory can also be used successfully to conduct in-service training. Individual topics can be taught separately, such as robot programming or explaining the functioning of the whole system. It is also possible to play through different scenarios that a customer may have in their production process.

The system left a number of options for further development, which will be done in the future. The system should be equipped with machine visioning to improve the robot arm capturing an objects, as well as AR (Augmented reality) technology to visualize factory planning and picking the goods from storage processes.

The completed system works and has been implemented in the study. The construction of the laboratory was funded by the Archimedes Foundation from program ASTRA.

Euroopa Liit
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Regionaalarengu Fond

Eesti
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Publication II

Vaher, K.; Kangru, T.; Otto, T.; Riives, J. (2019). The mobility of robotised work cells in manufacturing. 30th International DAAAM Symposium ''Intelligent Manufacturing & Automation'', 23-26th October 2019, Zadar, Croatia, DOI: http://dx.doi.org/10.2507/30th.daaam.proceedings.146

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THE MOBILITY OF ROBOTISED WORK CELLS IN MANUFACTURING

Kristo Vaher, Tavo Kangru, Tauno Otto, Jüri Riives

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DOI: 10.2507/30th.daaam.proceedings.146

Abstract

Many companies are already using robots, but many have not found enough applications for the robot and therefor they have not purchased it jet. One robot can be used to perform several different tasks, but it also raises the question of whether the production needs to be reorganized so that these multiple tasks are directed to the robot, or it can be solved differently where the robot moves between different tasks. In this paper different concepts will be discussed and each of its disadvantages and advantages will be highlighted. Paper also includes survey among Estonian manufacturing companies to find out which tasks are robotized and which tasks are desired to give over to robots in future. Paper also include short description about recently opened Industry 4.0 test hub where mobile robot applications are being tested and paper results will be also tested in this test hub. In general, this paper focus on solution how to use robot arm most efficient way if there is not enough job for stationary robot solution.

Keywords: Mobile robot, robot arm, manufacturing, industry 4.0

1. Introduction

One of the biggest problems of industry today is the shortage of qualified workforce. The development of technologies in the last decades has been extremely fast, the technologies today change much faster than generations. People from older generations often lack the knowledge and the courage to use the newest technologies. At the same time, children (and youngsters) from the younger generations lack the patience and willingness to study complicated engineering specialties. It is difficult to pinpoint the causes of this behaviour, but it is becoming clear that the industry must learn to deal with the situation and find new ways to keep the production ongoing and making profit in the future.

In order to alleviate the problem of qualified workforce, it is possible to use industrial robots and increase the automation of production. Robotization is, of course, more affordable to larger companies than to small and middle-sized enterprises (SMEs). The main precondition for using industrial robots is the production in large batches, especially in cases when there are multiple robots working simultaneously in the same system. Production monitoring system helps to identify the needed predictive maintenance and tool exchange times [1]. This, however, does not mean SMEs should not use robots at all. Collaboration robots can be successfully integrated into the work process of smaller enterprises, using interaction technologies [2]. Predictive simulations are used for fastest route planning in an industrial environment [3].

The development of collaboration robots and the general compliance of Industry 4.0 principles have made the implementation of industrial robots fairly easy [4], [5], [6], [7], [14].

One of the preconditions of operating an industrial robot is that it has enough working hours per day. In case of smaller enterprises that produce small batches, it would mean the reorganization of production so that the tasks performed by the robot would be directed to a stationary robot. Another option is to move manually the robot between different units of production. This may result in long pauses in working time and degrees of efficiency. The robot could, instead of waiting, fulfil another task or serve other benches. To achieve this, the production must be planned so that the benches the robot needs to serve are placed around the robot. Another option is to move the robot arm from one bench to another in the production area. It can be done by lifting it manually or by mobile robot.

In addition to the shortage of skilled labour, industries also have to deal with issues such as optimizing production times, using resources more efficiently, producing faster and smaller quantities, while ensuring high quality [13]. Robotic solutions are one of the key factor in solving these issues as well. Lack of knowledge to guide potential users of robotic sell is an essential barrier to more extensive use of robotised solutions [9].

2. Survey among Estonian Enterprises

In 2017, a survey was conducted among Estonian enterprises in order to map the level of robotization in production companies. Among other questions, the companies were asked about the characteristics of production in terms of batch sizes, in order to evaluate which companies could benefit from stationary and which from mobile robot cell solutions. 30 enterprises took part in the survey. The average size of the enterprises was 140 people, and according to turnover data, most of the companies could be defined as SMEs (small and middle-sized enterprises).

In addition, the survey included questions about batch/lot sizes of products and parts, and about the repeatability factor of a batch – meaning whether one part is produced multiple times or is every operation different. The survey showed that the batch sizes in 1/3 of the enterprises correspond to 10 – 50 units. In most cases, the repeatability of a batch was more than 50%. In case of batch sizes of less than 10 units, we could see a low repeatability level (ca 10%). With batches of more than 50 units, the repeatability level was high, more than 50%. Over 60% of companies answer that more that 50% of batches are repeated constantly over the time.

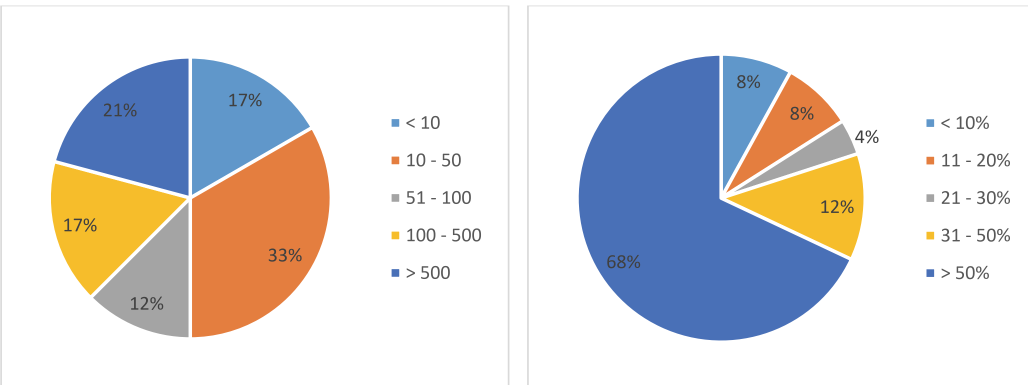

Fig. 1. Parts in lot size (left) and repeatability of the lots (right)

Based on the information from the survey, it can be concluded that most enterprises produce relatively small batches with high level of repeatability. This means that one bench is not only used for producing one product or part, and that products are being manufactured repeatedly. From the viewpoint of robotization, it means creating multiple programmes. When repeating the production cycle, a programme that has already been written can be used again.

The survey also indicates that the robots used in manufacturing are not fully occupied. Half on the enterprises use robots for up to 50-70% of their capacity. It shows that robots could be given additional tasks, but since the companies are using mainly welding robots, it is hard to assign other jobs for them. The data shows that only 25% of enterprises use more than 70% of their robots capacity.

According to the survey, up until now, industrial robots have mainly been used in welding operations. However, the data shows that enterprises would like to use robots for other operations as well, such as mechanical processing, painting, assembling and quality control (Fig. 2). In these areas, there are various tasks that can be assigned to one robot. If it is not possible to occupy a robot fully with a certain task, it is reasonable to use the robot for many different tasks.

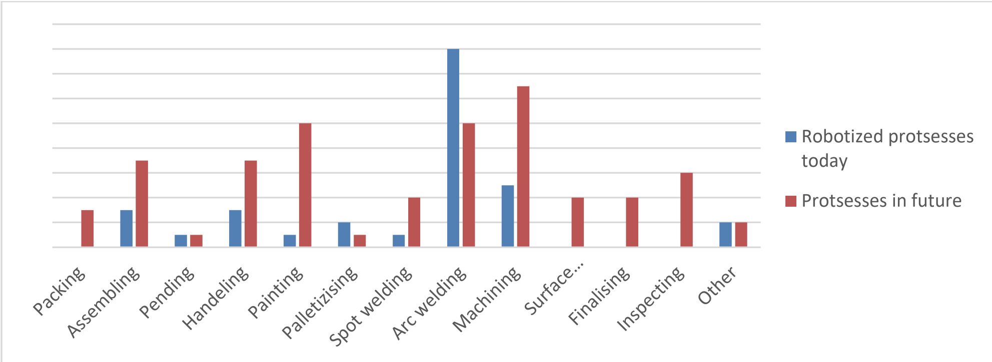

Fig. 2. Robotized protsesses today and desired processes for future

According to the Genefke scale, elaborated at Danish Technological Institute by Bo Genefke, the enterprises that took part in the survey mainly operate with tasks requiring standard and adaptable knowledge, which could be easily automated (Fig. 3). Genefke scale divides enterprises into five categories. The enterprises that belong to the first group can use standardized, easily applicable solutions. When moving to the right end of the scale, we see the complexity of tasks rising. The right end of the scale indicates enterprises who need completely new knowledge in their processes, such as enterprises and organisations dealing with research.

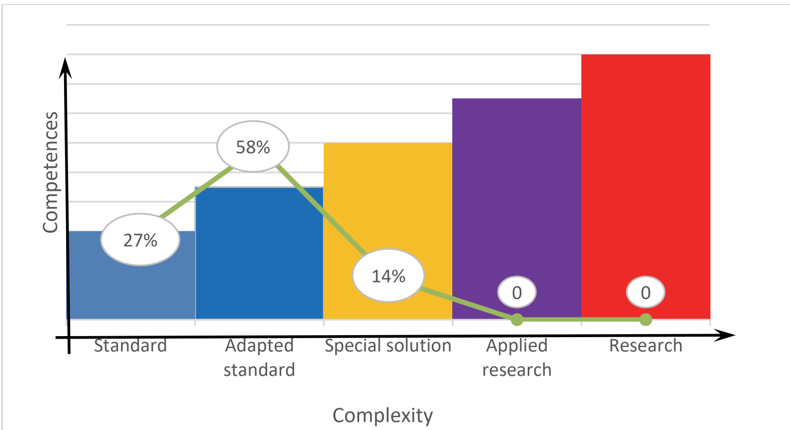

Fig. 3. Genefke scale

The survey conducted among Estonian enterprises shows that the robots used in production are mainly welding robots which are not used to their 100% capacity. At the same time, enterprises would like to use robots for other operations as well. The problem is that it is difficult to implement welding robots for other tasks, as their tool and installation is meant only for welding operations and it would be too costly to exchange those. Instead, it would be feasible to use a new robot for operations other than welding. In case the new robot cannot be fully occupied with one type of task, it would be beneficial to find a universal solution where the robot could perform different types of tasks, such as serving the CNC bench and packaging.

3. Manufacturing testbed for Industry 4.0

Most of the testbeds related research is related to cyber security and electrical grids, while robotics and manufacturing are in minority [10]. In current research the testbed for applying Industry 4.0 principles through robotics and manufacturing has been developed at TTK University of Applied Sciences [8]. The testbed laboratory features a functioning production system, starting from entering the order to Enterprise Resource Planning (ERP) until the pickup at the package station by an end consumer. In between, there is the whole manufacturing process together with several robots. The production system is modular and flexible. The system is easily reconfigurable when new products are added, and modules can be added or reconfigured when production volumes increase. Main purpose of this lab was to get test bed where different scenarios can be tested according to Industry 4.0 principles. Automatization components from Estonian manufacturers were also integrated to connect the concept regionally and also educate visitors and students.

One of the modules of this testbed manufacturing system is a mobile robot arm, the task of which is to serve all the other modules (Fig. 4). The main tasks of the robot arm include transporting the warehouse container between different modules and changing the plate in the 3D printer. In the testbed, similarly to state of the art international labs [11] robots from two different manufacturers have been used – the robot arm Universal Robots UR 10 and the mobile robot Mobile Industrial Robots MIR 100.

Fig. 4. Robot arm and mobile robot tandem.

Based on the mobile robotic arm module described above, practical tests will be conducted, and a prototype model developed for supporting the theoretical part of the current study. The aim is to build a base frame or a platform to the robot arm that would be separate from the mobile robot and that would be transportable by the mobile robot in the automated process together with the robot arm.

4. Alternative solutions for increasing the performance of a robot-cell

Today there are several different mobile robots available that are capable of moving the robot arm around in a room. For this, two different technologies must be combined. The result is a flexible solution that enables to use one robot arm in many working positions. There are solutions where a robot arm has been permanently installed into a mobile robot, such as KUKA KMR Quantec, KUKA KMR iiwa, Robotnik Kairos 3. In addition, there are many solutions of combining MIR 100 + UR10, and other robots from different manufacturers. In this case, the cost of the robot cell would be the sum of a robot arm and a mobile robot, therefore approx. doubling the cost.

However, the two work cells could be separated when, for example, more than one robot arm is used in manufacturing. In this case, one mobile robot can serve many robot arms. When combining a mobile robot and a robot arm, only one of them can work simultaneously with the other in most cases. During transport, the robotic arm is not working and when the robot arm is working, the mobile robot is standing idly. Separation of the tandem of a mobile robot and a robotic arm (fig. 5.) would considerably raise the efficiency of both units.

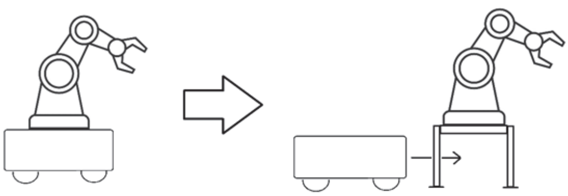

Fig. 5. Separating mobile robot from robot arm tandem

One industrial robot may easily be used for performing different working tasks. For this, a robot cell with different functionalities is needed. Many different tools can also be assembled to one robotic arm. For example, several work tools can be assembled to a robotic arm with a rotating multi-tool mount. Another option is to use a quick-change system (tool-change solution for immediate use). Using a rotatable multi-tool solution is a good and fast option, but its extra hardware and it add a lot of weight to the robot arm, which will therefore lower the maximum weight limit of the working task. The rotating multi-tool solution is being produced, for example, by New Scale Robotics. The advantage of a quick-change system compared to the rotatable multi-tool solution is its smaller weight. However, with this solution, less time will be left for the production process itself, as the change of the tool must be done in distance from the work object, therefore, it will take some time to detach a tool and replace it with a new one. Quick-change solutions are offered, for example, by the company Stäubli. Both solutions have their advantages and disadvantages and the choice depends largely on the implementation specialty and the characteristics of the working process.

Regardless of the type of a work tool of a robotic arm, the more important question is whether to bring the work tasks to the robot or to take the robot to the task(s). In case a robot will be brought into a working production facility, it is important to assess whether and how much will the system be reorganized and how much additional investments will be needed. The following pages focus on the three possible options of integrating robots with different working tasks.

4.1. Solution 1

In order to use one robot for many different operations, production should be planned so that the automated tasks are moved to the robot and the robot itself is stationary (Fig. 6.). In this case, the robot is the central object of production and everything else should be positioned accordingly. This would be a typical solution for a production facility using cage robots, where, in addition to the investment of buying a new robot, a security zone must be built around the robot. This is the option where the integration of a robot to an existing industrial environment will require a certain amount of reconfiguration. Production lines and other tasks should be moved towards the robot. In most cases, this means production would be stopped for a longer period of time.

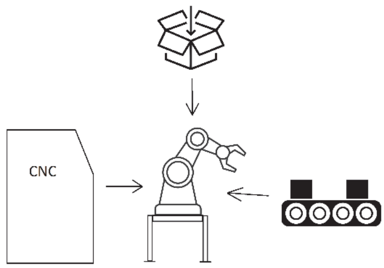

Fig. 6. Tasks directed to robot

4.2. Solution 2

The second option is to leave the existing production environment as it is and move the robot in between different working positions. In this case, the robot will be taken from one working position to another by a human (Fig. 7). The central object in the process is the human who has to be ready to move the robot at any time as soon as the production process requires. In this case, the manufacturing process will not change much. The moving of the robot requires the presence of a human, who will move the robot from one position to another in between working tasks. To employ an individual just for moving robots, however, may not be efficient. This solution may also cause time delays, at it may take time for a human to arrive to the robot after it has finished work. Similar solution was done by OpiFlex.

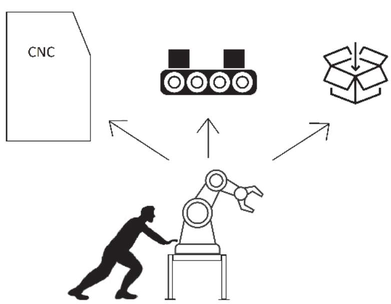

Fig. 7. Robot arm is moved between tasks by human

4.3. Solution 3

The third option is to automate the moving process of the robot arm by using a mobile robot (Fig. 8). With this solution, no part of the production takes the central role, as the whole process is fully automated and works as a compact whole. The manufacturing process can be planned with high accuracy level. For example, in case of a robot serving a CNC machine, it can be quite accurately calculated when the batch will be finished. By this time, a mobile robot can be sent to fetch the robotic arm, and it can be moved to the next task. In this option, there is no need for a human who would take the robot arm from one working station to another. Connecting the robot arm to the electricity network and other communications will take place automatically through the base frame of the robotic arm.
This solution presupposes that every working position need for the robot arm an automatic docking station, which has been linked with the centralized systems such as electricity, compressed air, data, etc.

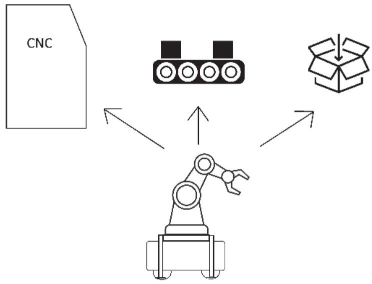

Fig. 8. Robot arm is moved between tasks by mobile robot

4.4. Comparison of solutions

The following charts (Table 1.) illustrate the levels of the changes that need to be done and the impact to the manufacturing process in case of different options of taking in use a robot arm solution. The chart does not bring out the factors that are similar for all the options, such as programming, implementation to the process, maintenance etc. Evaluation is done based on comparing those three solutions with each other and marks are given witch solution takes the highest credit and witch one the least.

	Need for reconfiguring the production	**Need for additional appliances**	**Need for additional software**	**Need for additional human work hours**
Solution 1	High	Low	Low	Low
Solution 2	Low	Low	Low	Medium
Solution 3	Low	High (mobile robot, dock's)	High (MES[1])	Low

Table 1. Integration needs for a robot solution implementation

The chart below (Table 2) compares the benefits of integrating a robot arm solution in factory. Case by case it can be different but in general it shows the different between those three solution results.

	Level of automation	**Rise of Efficiency level**	**24/7 (full time) working capacity**	**Flexibility**
Solution 1	High	High	High	Low
Solution 2	Medium	Medium	Medium	High
Solution 3	High	Rather high	High	High

Table 2. Benefits of integrating a robot arm to a production facility

[1] MES - Manufacturing execution systems

Different solutions require very different investments. Investing in automation is inevitable. New equipment and software must be introduced and money spent on programming. As a result, the goal is to achieve more efficient production. Efficiency gains are expressed differently by each company. It can be one of the factors in the table, or it can be all of the actions taken together. In solution three the score is high for all the factors. In future developments the testbed can be implemented for investigation of Industry 4.0 Digital maturity Model 4.0 [12].

5. Conclusion

Survey among Estonian companies brought out that implementation of industrial robots by SMEs has been slow. One reason for that is that, there is not enough work assignments for stationary robots without reorganize production in a big scale. At same time, the companies are interested to give more jobs to the robots. As a result of this work, a solution has been proposed in which the robot arm is moved between different working positions and the transport part is filled by another robot - a mobile robot. Such a solution can give high level of work hours to the robotic arm without the need to reorganize existing factory in big scale. When using a mobile robot, there is no need for a separate person who should take care to move the robot arm between different workstations. Carrying a robotic arm on a mobile robot gives you the opportunity to apply a robotic arm around the clock and it gives you flexibility to reconfigure your production more easily rather the solution where robot arm is stationary.

The aim of the thesis is to develop a technical solution for the mobile use of a robot arm, accompanied by a prototype and an assessment of its applicability. Further on, a design model will be developed for configuring a mobile robot to the robot arm. MIR 100 will be used as a mobile robot and UR 10 as a robot arm. A functional model and a cost-analysis will be developed. After this, a practical model will be built, and necessary tests completed for assessing the model's applicability.

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Publication III

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POSITIONING ERROR CORRECTION OF AUTONOMOUSLY MOVABLE ROBOT ARM

Industrial robots are mainly used stationarily in one working position. SMEs often find themselves in situations where robots don't have enough work to do, and because in general, robots cannot be easily moved to another position, the efficiency of robots will decrease. This study provides a solution for this issue. The solution can be found in a robot work cell where a mobile robot deals with robot arm transportation. However, since the mobile robot is not precise enough in positioning, machine vision is used to overcome this problem, which helps the robot to position itself accurately in relation to the work object. The solution has been developed and tested successfully at an Industry 4.0 testbed.

1. INTRODUCTION

Within all areas of robotics, the demand for collaborative and more flexible systems is rising [1]. Human-robot collaboration (HRC) has been active in the past to realize future manufacturing expectations. HRC has been made possible by several research results obtained during the past five to ten years within the scientific communities of robotics and automation [2]. Industrial robots are widely used in the industry, but there are also companies who have not been able to afford to buy robots. Mostly these are SMEs for whom buying a robot is a big investment and the investment has to pay back within a reasonable time. One of the reasons for not using a robot, according to a previous study [3], is the insufficient applicability of the robot in one working position. The company may not have enough work for the robot in one particular position in order to derive as much benefit from it as is possible. To achieve this, one would need to direct more robot operations to the robot or move the robot from one working position to another. In order to maximize the use of the robot arm in situations where there are not enough tasks in one workstation, the robot should be transported from one working position to another by

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a mobile robot. The task of a mobile robot would be transporting a number of robot arms on factory level. The digitalisation of industry is redefining the role of robots – they are expected to be mobile and collaborative. However, the problem with mobile robots is their low accuracy. Paijens et al. have elaborated the approach for odometry of mobile robots through the implementation and calibration of mouse sensors [4].

I.-M. Cheng has used linear error model to determine the error parameters in his research of rapidly reconfigurable robotic work cells [5]. Fujishima et al. have researched sensing interface board to solve thermal displacement compensation [6]. Dittrich et al. have worked on autonomous machine tool using adaptive process control [7].

This article aims to solve the problem of inaccuracy in repositioning a transportable robot arm, so that at each working position the robot arm could operate within its own working accuracy. The solution is to use machine vision which can detect markers and evaluate the offset of the robot's base coordinate. The development of collaboration robots and their general compliance with Industry 4.0 principles have made the implementation of industrial robots with other products fairly easy [8–12].

2. WORK CELL BASED ON INDUSTRY 4.0 METHODOLOGY

In 2018, an Industry 4.0 testbed was completed at TTK University of Applied Sciences [13]. The testbed was used for practical tests within the current research. Among other system components, the testbed includes the MIR 100 mobile robot and the Universal Robots UR10 industrial robot. The concept of the laboratory provided for the construction of a fully automated production system where human presence is not necessary. The production system is divided into modules: production, post-processing, automatic warehouse, delivery of goods, intralogistics. In the latter module, the mobile robot and the collaboration robot are working together. These two machines are physically interconnected in a manner in which the mobile robot transports the robot arm between different modules (Fig. 1). Each module has specific tasks for the robot arm.

Fig. 1. The tandem of robot arm and mobile robot

The robot tandem is able to work independently, but its work is constrained by low accuracy. The main problem is the different accuracy of the two machines. The robot arm can reposition itself within ±0.05 mm. The positioning accuracy of the mobile robot is ±10.0 mm if it is using positioning marker. Without it, the accuracy is even worse, ±50.0 mm. Due to the low accuracy class of the mobile robot, its positioning error is transmitted to the work of the robot arm and the accuracy of the robot arm equals with the accuracy of the mobile robot. This considerable difference causes a problem for the robot arm, as the robot's job is to pinpoint certain objects where the accuracy must be about ±1 mm.

The positioning accuracy of the mobile robot cannot be improved to the level of the robot arm. The solution to the problem should come from an external device or sensors. Therefore, the authors have proposed to use machine vision to detect markers and evaluate the offset from zero condition. Markers must be installed at each working position and each marker must be rigidly linked to the location where the work is to be performed. Each time the robot enters a working position, a shift in the mobile robot relative to the working position is detected.

The camera must be mounted to the robot arm close to tool location. In each working position, the robot arm moves above the marker and takes a picture of it. The difference in coordinates (X, Y, angle) between the position of the initially trained marker and the new position is calculated and added to the base coordinate of the robot arm. In this way, the robot arm always works with the same program and with the same precision. The positioning accuracy of the mobile robot with a marker is ±10.0 mm – small enough in the camera's field of view to fit inside the detection area. Z-axis measurement is not important due to the fact that the height of the mobile robot is not changing during the positioning.

3. RESEARCH SETUP

The camera that was used in the experiment was Cognex IS2000M-130-40-00 with 25 mm lens. The camera has monochrome image recognition (black and white). The focus length is manually adjustable, which meant that the same marker was detected exactly at the same distance for all the detection points. In this project, the detection distance was set at 30 cm.

Next to each working position, an L-shape sticker (Fig. 2) was added, rigidly connected to working stations such as the 3D printer or the parcel cabinet. L-sticker was used to define the position of the mobile robot in relation to the working station. Each time the mobile robot entered a working position, the L-sticker was captured with camera and the offset from zero position was calculated and added to the program of the robot arm.

A new program for a new location could be programmed with the UR control panel. The *Camera_Start* subroutine had to be chosen at the beginning of the UR program. The camera that has a manually adjustable focus point had to be positioned over a subject (300 mm). *Stop* command had to be selected at this point. After that, the *camera trigger* subroutine had to be called. After triggering the camera, three variables (*fixX*, *fixY* and *fixA*) occurred, these variables had to be noted.

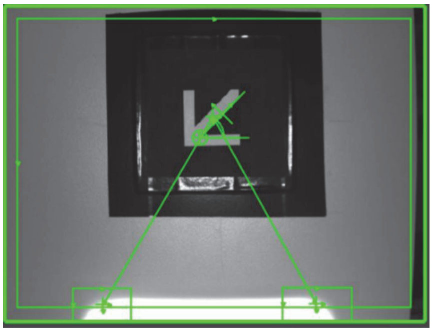

Fig. 2. L-sticker deduction with camera (In-Sight Explorer)

Because the Cognex URCAP caused the robot to stop working, the robot communicated with the RPC server, which in turn communicated with the camera via *telnet*. The RPC server is configured to port 555 and has 3 features:

- *start_camera_telnet*: This function must be executed in the UR in any program that requires communication with the camera. The function expects no values and returns either 0 (communication with the camera failed) or 1 (communication with the camera succeeded).
- *change_camera_job*: Function can be used to change the camera job if needed. It waits for one value (the job number) and returns one of three options – 0 (camera job exchange failed), 1 (camera job exchange succeeded), or 2 (the camera already had a job and nothing was changed).
- *trigger_camera*: The function can send a capture command and does not expect any value. FUNCTION returns one of three options, "0,0,0" (failed to send command to camera), "1,0,0,0,0" (failed to send command to camera, the camera did not finish the job successfully), or "1, x, y, angle, 1" (command was successfully transmitted to the camera, coordinates of the object were detected and the camera job succeeded). The given X and Y are relative to the camera.

The camera used in the current research does not have an ability to position the object in a form where we can read out X- and Y- coordinates. It only has the ability to detect objects and measure distances between them. Therefore, we attached an object that would always be in the same position in relation to the camera (Fig. 3).

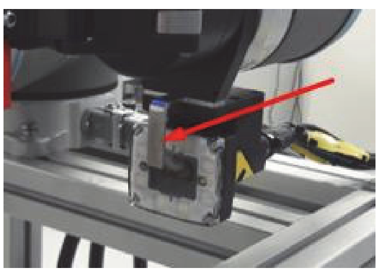

Fig. 3. Permanent object in front of camera

The following settings were set up on the camera (Fig. 2. on the right):

- Marker recognition.
- Detecting the left corner of the subject attached to the camera.
- Detecting the right angle of the subject attached to the camera.
- Measuring the distance between the sticker and the left corner.
- Measuring distance between the sticker and the right angle.
- Measuring the angle of the camera and the subject on the camera.

If all the objects were successfully identified, the results were transmitted to the RPC server. If we got to know the distances between the angles of the object on the camera (the *X*- and *Y*-coordinates of these angles were also known to us in advance) then we could calculate the position of the L- sticker on the camera's axis.

There are three sub-programs for using the camera:

- *Camera_Start*: this programme needs to be run before using other camera functions.
- *Camera_Trigger*: the program sends a capture command to camera and receives new *X*, *Y* and angles in response.
- *Camera_Change_job*: changes the camera job. Variable jobID: must have the number of the corresponding job.

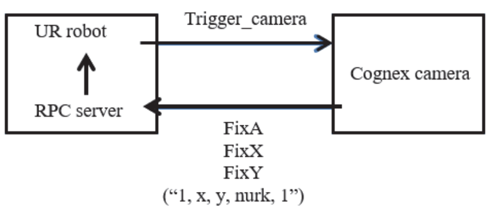

Fig. 4. Communication between camera and RPC server

To measure the positioning accuracy (ability to repeatedly position at same coordinates) of the mobile robot, a one-millimeter graph paper was placed onto the work surface, where the robot arm would make marks. The marks where made with three different positioning methods - positioning without a marker (Test #1), positioning with a VL- marker (Test #2), positioning with machine vision (Test #3). The number of marks made in each position was 50. The bigger amount of marks did not give better results in terms of dispersion. The mobile robot moved between positions in an automatic mode (Fig. 5).

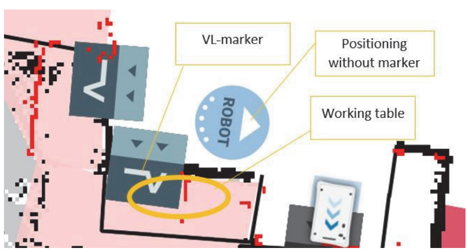

Fig. 5. A laser scanned map of the MIR robot with positioning points

Graph paper had three different areas where markings were made. Area # 1 (Fig. 6.) was for the robot positioning without the marker, area # 2 was for the VL- marker positioning and area #3 was for the machine vision positioning. All marks where measured and transferred to an excel file.

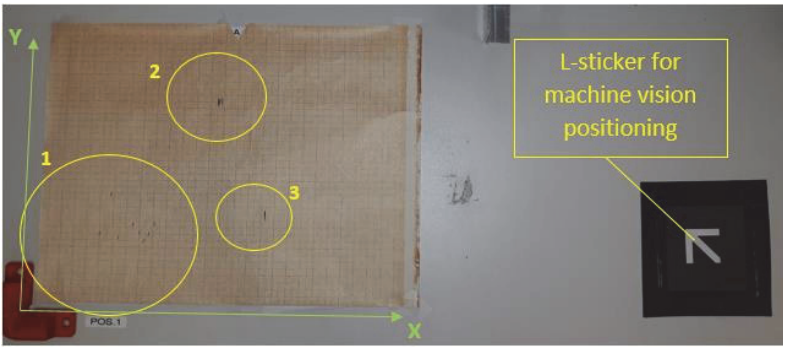

Fig. 6. Working table

For machine vision test, the following mathematical approach was given to the UR program to consider with data coming from Cognex camera:

$$nurk := (firstA - fixA) * -1$$

$$Base\_var := p[0,0,0,0,0,nurk]$$

$$addX := \frac{firstX - fixX}{1000}$$

$$dddY := \frac{firstY - fixY}{1000}$$

$$pose\_add(Base\_var, p[addX, addY, 0,0,0,0])$$

Fig. 7. Angle correction formula (left), coordinates X and Y correction formula (right)

4. POSITIONING ACCURACY ANALYSIS

4.1. POSITIONING WITHOUT THE MARKER

Test # 1 – mobile robot positioning without positioning marker

In case positioning without a positioning marking, the positioning accuracy of the mobile robot was poor. According to the information provided by the manufacturer, the positioning accuracy is +/-50 mm. The mobile robot positions itself with laser sensors measuring distance from surrounding objects like walls, and compares the obtained measurement with a previously stored map (all black lines on the map, Fig. 5). The result of positioning by this method was found as the result of the test in Test # 1 (Figs. 8, 9).

The results of this experiment showed that by positioning freely on the map without a marker, the robot can reposition itself in *X*-axis +/-50 mm and in *Y*-axis +/-45 mm. Therefore, the data given by the manufacturer is correct.

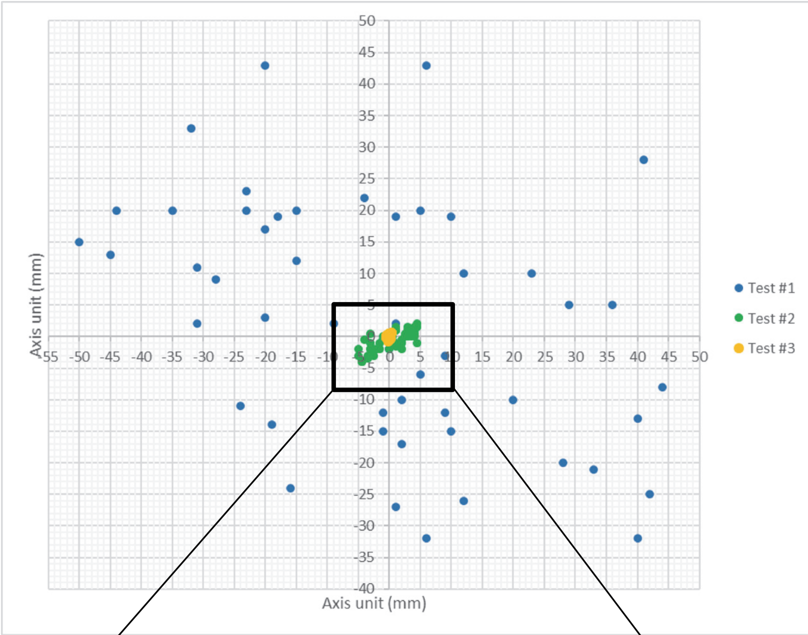

Fig. 8. Results of the three different tests

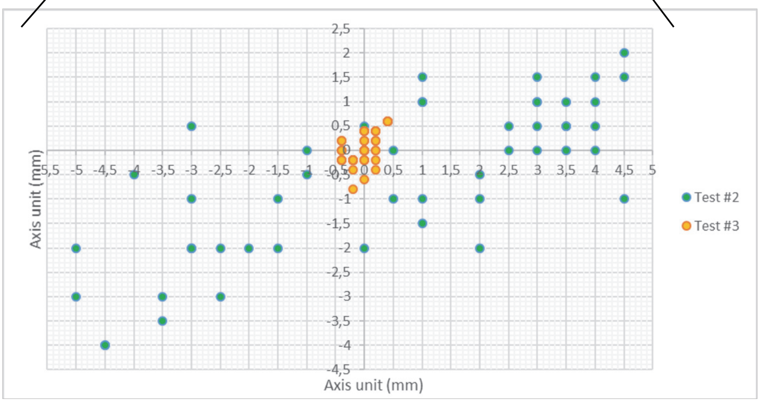

Fig. 9. Zoom in, view of two tests Fig. 8

4.2. POSITIONING WITH VL-MARKER

Test # 2, mobile robot positioning with VL-marker

The VL- marker is a method provided by the manufacturer for more accurate positioning of the mobile robot. The VL- marker is basically a wall with a V-shaped cavity. The distance between the two sides of the cavity are measured constantly by the laser while approaching that cavity. The position of the mobile robot is constantly adjusted. With such a marker, according to the manufacturer's information, the robot can position itself with an accuracy of +/-10 mm.

The results of the experiment showed that by using the VL- marker, the robot is able to reposition itself on the *X*-axis with an accuracy of +/-5 mm and on the *Y*-axis with an accuracy of +/-3.5 mm.

4.3. POSITIONING WITH MACHINE VISION

Test # 3, robot positioning with machine vision

Position for the machine vision is detected at the location of the mobile robot in the VL- marker. The repeatability of positioning to this marker is given in the previous chapter.

The results of the experiment showed that by using machine vision, the mobile robot is able to reposition itself on *X*-axis direction with an accuracy of +/-0.5 mm and on the *Y* axis with an accuracy of +/-1.0 mm.

The large error (+/-1.0 mm) towards *Y*-axis resulted from the setup of the machine vision parameters. This error probably came from the angle measurement of the L-sticker. It was not very precise due to the fact that pixels were converted to millimeters. This small error was also shown on the first picture, where the camera position angle was adjusted, also effecting *X*- and *Y*- coordinates that were taken with the next picture. Therefore, more precise measurement of the angle needs to be established to correct the conversion of measures.

5. CONCLUSION

In earlier work on robotised work cells [3], the reasons were found that prevent SMEs from adopting robots, and various variants of robot implementation in enterprises were proposed [3]. It was found that the best solution for SMEs is to obtain a robot that can be moved from one job position to another at the factory level, and this should be done with an automated mobile robot.

Adding a Cognex camera to the Universal Robots robot arm is technically easy and requires little programming. Cognex and UR work well together even though the Cognex application for the UR robot interface is inapplicable. This issue was resolved by using scripts written to the server of the UR robot controller. Scripts were triggered in the UR program when needed.

Machine vision significantly improved the accuracy of the robot arm despite the inadequate positioning accuracy of the mobile robot. With machine vision, a repeat accuracy of +/-0.5 mm for the robot arm was achieved. The robot arm itself has an accuracy of +/-0.05 mm, but the result of using machine vision was sufficient enough to perform most of the tasks.

The further aim of work on robotised work cells is to achieve a result where the robot arm would be separated from the mobile robot and both machines would be capable of operating independently from each other. The task of the mobile robot would be to transport several robotic arms on factory level. In the scope ot this article, the problem of inaccuracy in repositioning a transportable robot arm was solved: in each working position, the robotic arm could work within its own accuracy regardless of how accurately it was trasnported to the working position.

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Publication IV

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MANUFACTURING
ENGINEERING

Simulation based feasibility analysis of autonomously movable robot arm

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Abstract. The use of industrial robots in production is rapidly growing. However, the vast use of industrial robots and implementation of new manufacturing technologies are mostly adopted by large industrial companies. It is due to the nature of the production volume, as robots perform a fair amount of the same work in one specific position in the production process. In smaller companies where robots do not often have sufficient workload in a single specific workplace, the process of robotization has not been so successful. SMEs (small and medium-sized enterprises) need a solution how the robot can be moved from one workplace to another in order to utilize the resources, such as a robot arm, efficiently. This paper aims to analyse the feasibility of the usage of a robotic arm (a collaborative robot) to serve more than a single production cell intermittently. Production machines are located at a particular distance from each other and the movement of the robotic arm between the machines is carried out autonomously with the help of an autonomous mobile robot. Simulation and 3D visualization were used to conduct and analyse two different scenarios of an autonomously moving robot. Utilization of production equipment was considered as a key performance indicator.

Key words: Industry 4.0, industrial robots, cobots, smart machines, machine vision.

1. INTRODUCTION

In manufacturing industry automation via robots for different applications is inevitable. The recent evolvement of the Industry 4.0 concept and new industrial communication technologies such as the Internet of Things in manufacturing have led the automation to the autonomous level.

The applications of industrial robots (industrial robots are automated, programmable and capable of movement on three or more axes) are observed mainly for repetitive and high-precision tasks or monotonous tasks demanding physical effort. The development of collaborative robots ensures safe working conditions for human workers and allows human workers to confidently share the workspace with robots [1]. It means there is omission of fences for industrial robots and utilization of space can be increased on the factory floor. The new industrial robots can have an ability to move freely and execute several complex activities like humans do [2]. Furthermore, free movement of cobots (collaborative robots) on the shop floor enables better utilization of the surface area in production as well as enhanced usage of resources, possible reduction in costs for automated cells, timely and easier access to the process machines, and lower downtime. It may encourage smaller companies to implement robotic solutions [3]. One of the possibilities to autonomously move a robotic arm among several machines is to

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use the Autonomous Mobile Robot (AMR) platform and mount a robot arm on the AMR. Calibration of the robot arm's position relative to the workstation was solved in our previous article [4].

Analysing a change or testing a solution can be performed digitally by creating a similar-scale virtual environment and simulating it. In the digital manufacturing context, the use of simulation tools allows for the performance evaluation of manufacturing systems and production cells with the help of certain performance indicators [5,6]. In this case, there is no need to acquire physical resources and the changes can be validated through a digital manufacturing approach [7].

Relevant literature has analysed the need for mobility generated by industrial robots [8,4] and identified possible solutions for it. The solutions for moving a robot manually by a human or automatically by a mobile robot were evaluated in [8]. The automatic positioning accuracy of the robot arm moved by the mobile robot was analysed using machine vision [4]. Interesting approach was suggested [9] for replacement of manual work by hybrid production by means of autonomous dual arm robots, enhancing operator's working conditions and maintaining the same production levels. Nielsen et al. showed [10] that mobile robot arms can continuously perform meaningful industrial tasks such as the so-called bartender concept in cloud manufacturing (CMfg).

This article evaluates the efficiency and cost-effectiveness of a solution where the robot arm is moved by the mobile robot. A 3D simulation software was used for this purpose. The aim of the simulation was to analyse different production scenarios of an autonomously moving robot and to compare them with a situation where people perform the same work.

This research was carried out in the framework of the development of semi-industrial Industry 4.0 Lab, involving a robotised production line, 3D printing stations and an automatic storage system (see Fig. 1).

2. DESCRIPTION OF SIMULATION

In this simulation (Fig. 2), the Robot Arm (RA) was moved from Work Position 1 (WP 1) to Work Position 2 (WP 2) by the Mobile Robot (MR). Upon arrival at its work position, the robot arm positioned itself relative

Fig. 1. Semi-industrial Industry 4.0 Lab with autonomous cobot platform.

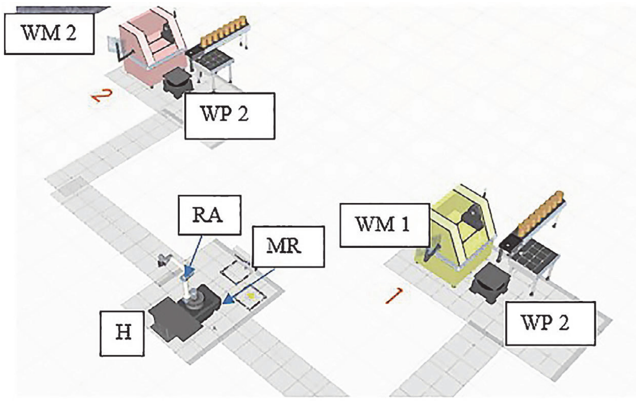


Fig. 2. Robot arm (RA) moved by mobile robot (MR) between working positions (WP 1, WP 2). WM 1 and WM 2 are working machines, H is the home position for mobile robot.

to the workplace using machine vision. Once the position had been detected, the robot arm connected itself to the communication network by a special plug. The start signal was transmitted to the Manufacturing Execution System (MES), which in return sent the correct command to start the correct program inside the robot arm controller. Communication between the MES and the RA and the MR was made via WiFi (IEEE 802.11). At the end of the work process, the robot disconnected itself from the communication network, transmitted a signal that the work was finished and waited to be transported to the next task. The whole process took place without human interaction.

Two different use cases were analysed. Use case A is a common way of how the robot arm is utilized by SMEs. Use case B is a new method proposed by us, where the robot arm is moving constantly between WPs to execute tasks and reduce downtime.

2.1. Use case A

- Two workplaces, one robot arm, one mobile robot.
- Lot size of 8 pieces (parts that are produced with the machines, see Table 1).
- Operation time for Machine 1 is 3 minutes per part and for Machine 2 it is 5 minutes per part.
- All parts are produced first in Working Machine 1 (WM 1) and then in Working Machine 2 (WM 2). The robot stays with Machine 1 until the parts are ready and then moves to Machine 2 and stays there until all the parts are completed.
- The mobile robot leaves after it has moved the robot arm.

Table 1. Input data for mathematical analysis

Name	Value	Formula unit
Lot size	8 pieces	x_1
Time to insert a part into WM with RA	15 s	x_2
Time to take out a part from WM with RA	20 s	x_3
RA positioning time	30 s	x_4
MR movement time from (H) to WM 1	20 s	x_5
MR movement time from (H) to WM 2	20 s	x_6
MR movement time from WM 1 to WM 2	50 s	x_7
Working time of WM 1	180 s	x_8
Working time of WM 2	300 s	x_9

2.2. Use case B

- Two workplaces, one robot arm, one mobile robot.
- Lot size of 8 pieces (parts that are produced with the machines).
- Operation time for Machine 1 is 3 minutes per part and for Machine 2 it is 5 minutes per part.
- Machines 1 and 2 are working simultaneously. The robot arm is moving constantly between Machine 1 and Machine 2.
- The mobile robot leaves after it has moved the robot arm.

The data collected from the use cases include working hours of the mobile robot, robot arm and working machines. In parallel, a mathematical calculation was performed with parameters (given in Table 1) for the use cases and compared with the simulation results.

3. SIMULATION DATA ANALYSIS

The set of data obtained from the Visual Components analysis is presented graphically in Figs 3–4. Comparison of the WM 1 and WM 2 utilization in use cases A and B shows that the utilization for use case A is very low but very high for use case B, close to 90%. At the same time, a large decrease in production time can be seen. The production time for use case A is 68 minutes and for use case B it is 44 minutes, i.e. the production time is reduced by approx. 35%.

As regards use case A, the determination of the use of a mobile robot is very low. The average utilization of the MR is 3.8%. For use case B the utilization is much higher, 37.5%, being roughly 10 times higher. The robot arm utilization time is given as the sum of both work positions (WP 1 and WP 2). The utilization for use case A is low, 3.7 %. This is due to the fact that the RA does not work during the working hours of the WM. In use case B the RA is constantly moved between the two WPs and the RA utilization is increasing almost 2 times. The average utilization of the RA for use case B is 6%.

In addition to the Visual Components simulation, the results were also analysed mathematically. In regard to different use cases, the operating time and idle time of the devices were calculated, and calculations of the operating time and utilization were made on the basis of them (see Tables 2–3).

$$RA_{wh.A} = \frac{(x_2+x_3)\times x_1+(x_4\times 2)+(x_2+x_3)\times x_1+(x_4\times 2)}{3600}\ , \tag{1}$$

$$RA_{wh.B} = \frac{(x_4\times x_1\times 2+x_2\times x_2+x_3\times x_1)+(x_4\times x_2\times 2+x_2\times x_1+x_3\times x_2)}{3600}, \tag{2}$$

$$MR_{wh.A} = \frac{(x_5\times 3+x_7+x_6\times 3)}{3600}\ , \tag{3}$$

$$MR_{wh.B} = \frac{(x_5+(x_5+x_7+x_6)\times(x_2-1)+(x_6+x_7+x_5)\times x_1}{3600}, \tag{4}$$

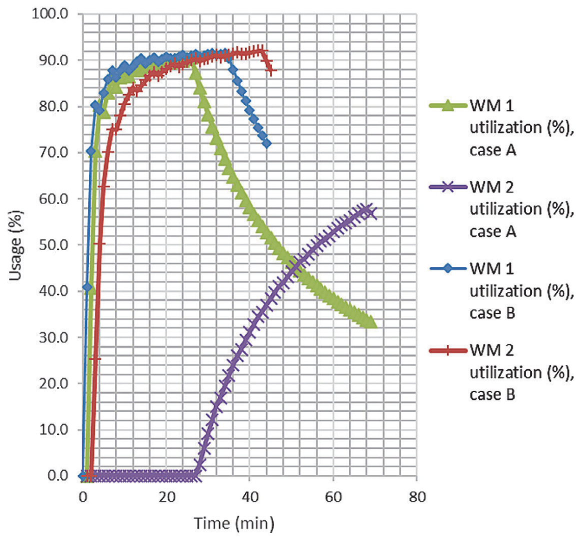
$$Total\ process\ time_A = \frac{(x_8\times x_2+x_9\times x_1)+(x_5+x_4\times 2+x_7+x_4\times 2+x_6)+((x_2+x_3)\times x_1\times x_2)}{3600}, \tag{5}$$

$$Total\ process\ time_B = \frac{(x_9\times x_1)+((x_4+x_2+x_3+x_4)\times x_1\times 2)}{3600}\ . \tag{6}$$

Average utilization time for the RA and the MR is calculated as follows:

$$RA_{ut.x} = \frac{RA_{wh.x}\times 100}{Total\ process\ time_x} \qquad MR_{ut.x} = \frac{MR_{wh.x}\times 100}{Total\ process\ time_x}\ . \tag{7}$$

(a)



(b)

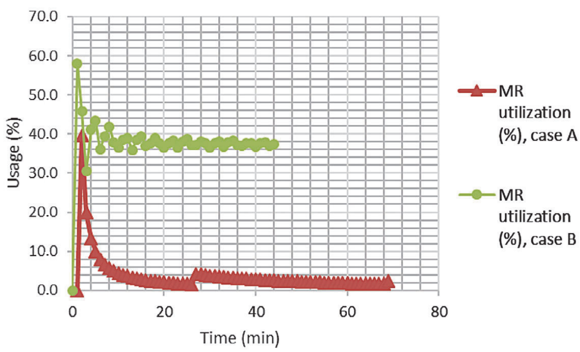


Fig. 3. Working machine utilization (a) and mobile robot utilization (b).

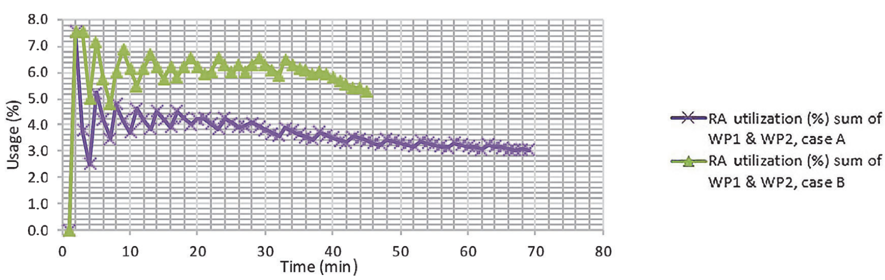


Fig. 4. Robot arm utilization.

Table 2. Working and idle hours of RA and MR

Use case (x)	RA_{wh}	MR_{wh}	RA_{ih}	MR_{ih}
A	0.19	0.05	1.09	1.07
B	0.42	0.38	0.23	0.78

wh – working hours.
ih – idle hours.

Table 3. Utilization of RA and MR

Use case (x)	RA_{ut}	MR_{ut}	Total process time
A	14.8%	3.7%	1.28
B	38.8%	34.9%	1.09

ut – utilization, working time calculated from total time (%).

There are some differences between the simulation and the mathematical computer because it is not possible to enter certain time parameters for the operation of the RA in the visualization program. A mathematical model provides more accurate results than a simulation. Input data units are in seconds. Output values are given in hours.

The results of the simulation and mathematical calculation are different. The reason is that the simulation software does not have the option for adding additional time for RA adjustment before starting work with the WM. The mathematical calculation of use case B compared with use case A indicates that the time required for production decreases by about 20% and the use time of the RA and MR devices increases significantly by about 2 times.

By changing the input parameters of the process, the performance indicators also change. Extending the working time of the WM significantly reduces the total production time for use case B compared with use case A. By increasing the distance between the working machines, i.e. by increasing the travel path of the MR, the production time as well as the utilization rate of the RA and the MR decrease for use case B.

4. CONCLUSIONS

The use of industrial robots in SMEs has been modest so far, one of the reasons being the lack of work for the robot in one particular location. Moving the robotic arm between working positions would significantly increase its usability and increase the rate of use of the device itself. This article has compared two different ways of using a robot, the second of which (use case B) allows the robot arm to move autonomously between different workstations on the factory site with the help of a mobile robot. Autonomous movement of the robot arm between different work positions significantly increases the usability of the robot and increases production efficiency. As a result, a virtual production line was added to semi-industrial Industry 4.0 Lab, allowing better pre-planning and faster reconfiguration without stopping the real time production.

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Autonoomselt liikuva robotkäe simulatsioonipõhine teostatavusanalüüs

Kristo Vaher, Kashif Mahmood, Tauno Otto ja Jüri Riives

Tööstusrobotite kasutamine tootmises kasvab kiiresti. Tööstusrobotite laialdast kasutamist ja uute tootmistehnoloogiate kasutuselevõttu edendavad enamasti suured tööstusettevõtted. See on tingitud tootmismahu iseärasusest, kuna robotitel on tootmisprotsessis ühes kindlas positsioonis palju sama tüüpi tööd. Väiksemates ettevõtetes, kus robotitel pole ühes töökohas sageli piisavalt töökoormust, pole robotiseerimisprotsess olnud nii edukas. Väikese ja keskmise suurusega ettevõtted (VKE-d) vajavad lahendust, kus robotit saab ühest töökohast teise viia, et ressursse nagu robotkäpp tõhusalt kasutada. Selle artikli eesmärk on analüüsida robotkäe (koostööroboti) kasutamise otstarbekust, teenindada rohkem kui üht tootmisseadet. Tootmismasinad asuvad teatud kaugusel ja robotkäe liikumine masinate vahel toimub autonoomse mobiilroboti abil. Lisaks kasutati kahe erineva stsenaariumi läbiviimiseks ja analüüsimiseks simulatsiooni ja 3D-visualiseerimist. Uurimuses võrreldakse erinevate masinate kasutamismäära erinevates situatsioonides.

Publication V

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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.

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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].

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.

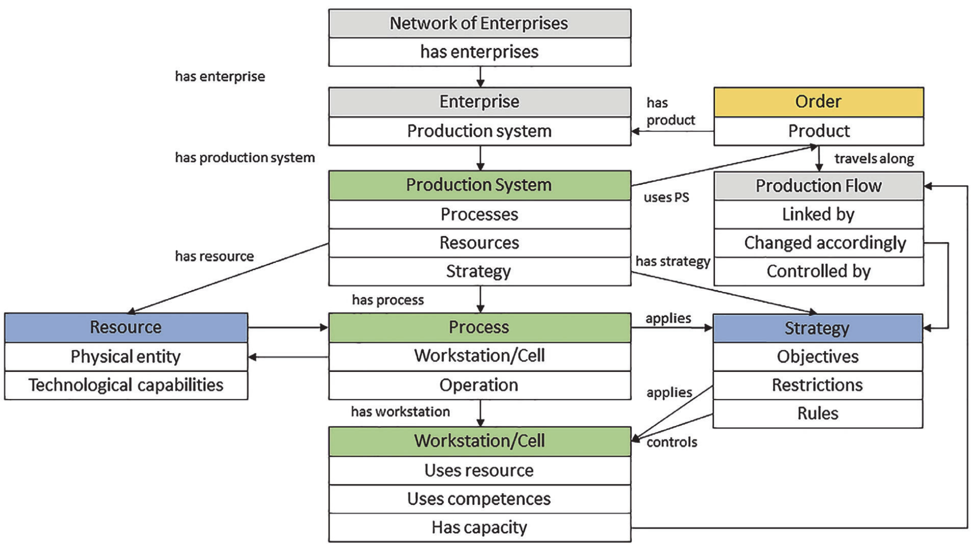

Fig. 1. Ontology in manufacturing [4]. PS − Production System.

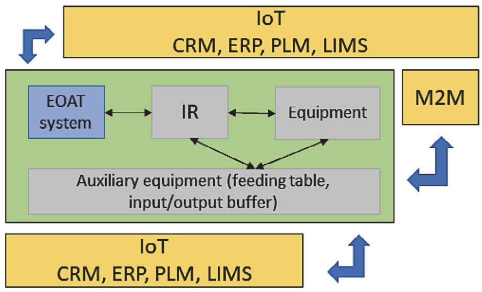

Fig. 2. Robot cell with CPS functionality. CRM – Customer Relations Management; ERP – Enterprise Resource Planning; PLM – Product Lifecycle Management; LIMS – Laboratory Information Management System; EOAT – End-of-Arm Tooling.

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

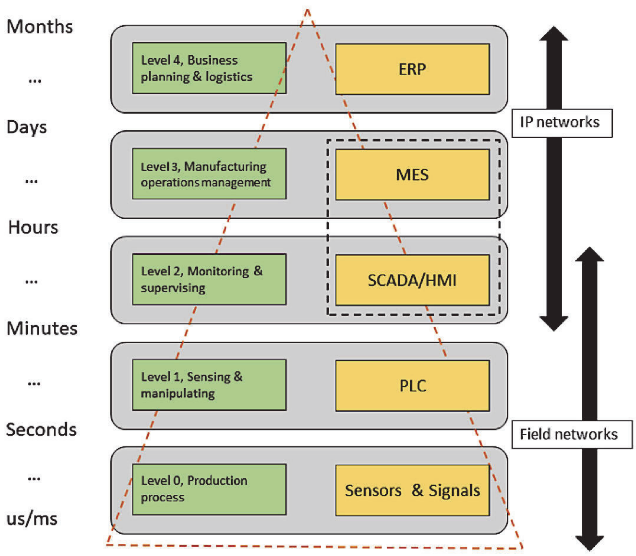

Fig. 3. Integration and connectivity in manufacturing according to ISA-95.00 [6]. SCADA – System Control and Data Acquisition; HMI – Human-Machine Interface; PLC – Product Life Cycle.

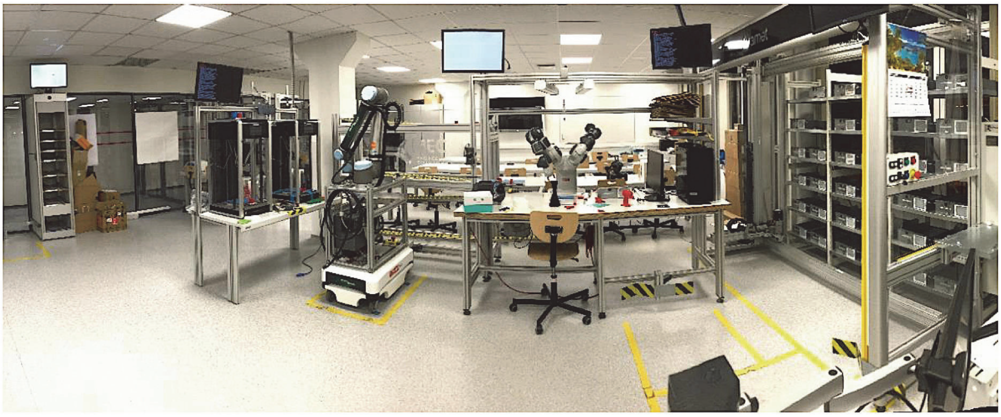

Fig. 4. TTK Industry 4.0 CPS.

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

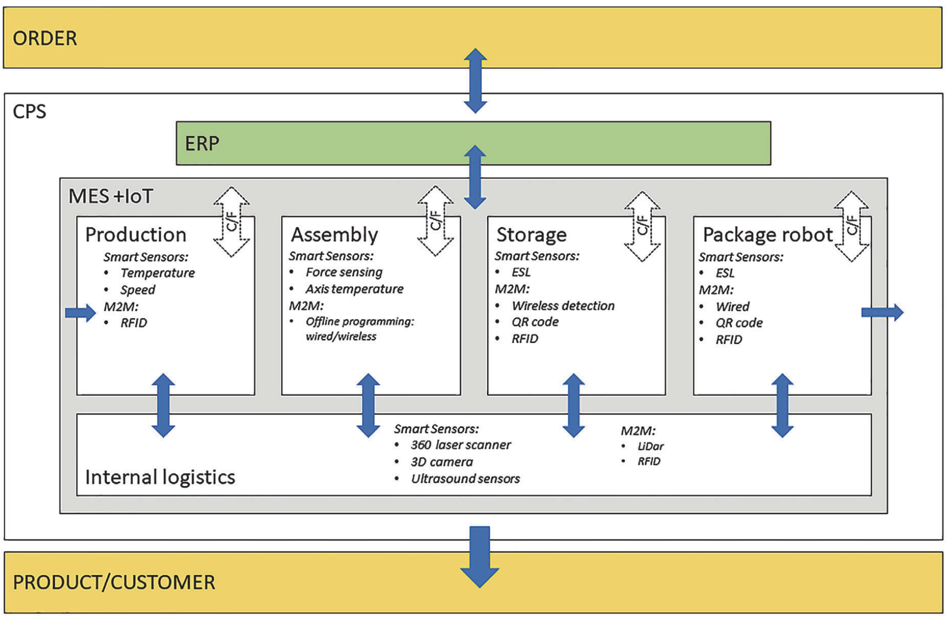

Fig. 5. Developed system's schematic diagram. ESL – Electronic Shelf Label; RFID – Radio Frequency Identification.

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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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.

Patent application

Patendi saamise avaldus

Käesolevaga soovitakse saada patenti Eesti Vabariigis

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Taotleja on saanud patendi taotlemise õiguse kui isik vastavalt töölepingule

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Eesti keeles:	Transpordisüsteem koostööroboti autonoomseks teisaldamiseks eri tööpositsioonidele ja täpseks positsioneerimiseks eri tööjaamadel
Inglise keeles:	Transport system for autonomously moving between different working locations and precisely positioning of the collaborative robot at different working stations

Lisad

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Direct link https://www.etis.ee/CV/Kristo_Vaher/eng/

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