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Intelligent self- and reconfigurable manufacturing system

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Good stuff

Abstract

Over the past few years, the market has shifted away from mass production towards mass customization and personalized production. This shift has made it necessary for manufacturing companies to change their manufacturing line more frequently, which can be both expensive and time-consuming. To overcome this challenge, reconfigurable manufacturing systems (RMS) have been proposed as a solution. However, there are numerous challenges associated with RMS, including a lack of research on physical implementation and automating the system, designing a new layout due to complexity, and time-consuming reprogramming of robots and other machines.

This research addresses the gaps and challenges in the physical implementation and automation of RMS. A physical platform-based RMS has been developed, which can be reconfigured automatically without any human intervention. The system uses a mobile robot to move and reconfigure different platforms, which has led to the concept of a highly flexible RMS being proposed.

Furthermore, this research investigates the impact of Industry 4.0 technologies on RMS. The study involves integrating additive manufacturing, advanced robotics, industrial big data, digital twin and simulation, and industrial internet of things (IIoT) into the physically highly flexible RMS to enhance its efficiency and performance. Wireless power transfer (WPT) is also proposed as an Industry 4.0 technology to wirelessly electrify the highly flexible RMS. Additionally, multiple Industry 4.0 technologies are used together to address the issues of layout design and reprogramming of RMS. This includes the proposal of a smart layout design system and a framework for developing an intelligent and self-RMS.

The main contributions of the research are:

- Proposing the concept of a highly flexible RMS and demonstrating how such a system can be built.

- Investigating the impact of Industry 4.0 technologies, such as additive manufacturing, advanced robotics, industrial big data, digital twin and simulation, IIoT, and WPT, on RMS.

- Using multiple Industry 4.0 technologies to propose solutions to the layout design problem of RMS and proposing an intelligent self-RMS.

Overall, this research provides practical solutions for designing and operating reconfigurable manufacturing systems, making it easier for manufacturing companies to adapt to the shift toward mass customization and personalized production.

List of Included Papers

Number	Publications
Paper 1	"Reconfigurable autonomous industrial mobile manipulator system", Halldor Arnarson and Bjørn Solvang, 2022 IEEE/SICE International Symposium on System Integration (SII), 2022, pp. 772-777, doi: 10.1109/SII52469.2022.9708887.
Paper 2	"Towards automatic configuration and programming of a manufacturing cell", Halldor Arnarson, Hussein Mahdi, Bjørn Solvang, Bernt Arild Bremdal, Journal of Manufacturing Systems, Volume 64, 2022, Pages 225-235, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2022.06.005.
Paper 3	"Reconfigurable 3D printing platform for warehouses", Halldor Arnarson, Mathias Sæterbø, Natalia Khan, and Bjørn Solvang, 2023 27th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Accepted.
Paper 4	"Towards automatic generation of image recognition models for industrial robot arms", Halldor Arnarson, Bernt Arild Bremdal and Magnus Fredheim Hanssen, 2023 27th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Accepted.
Paper 5	"Reconfigurable Manufacturing: Towards an industrial Big Data approach", Halldor Arnarson, Bernt Arild Bremdal and Bjørn Solvang, 2022 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2022, pp. 632-637, doi: 10.1109/AIM52237.2022.9863341.
Paper 6	"Investigation of wireless electrification for a reconfigurable manufacturing cell", Hussein Mahdi, Halldor Arnarson, Bjørn Solvang, Bernt Arild Bremdal, Journal of Manufacturing Systems, Volume 67, 2023, Pages 379-388, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2023.01.002.
Paper 7	"Towards smart layout design for a reconfigurable manufacturing system", Halldor Arnarson, Hao Yu, Morten Monland Olavsbråten, Bernt Arild Bremdal, Bjørn Solvang, Journal of Manufacturing Systems, Volume 68, 2023, Pages 354-367, ISSN 0278-6125, https://doi.org/10.1016/j.jmsy.2023.03.012.
Paper 8	"Intelligent and self- reconfigurable manufacturing system", Halldor Arnarson, Syed Abdur Rahman Tahir, Beibei Shu, Bernt Arild Bremdal, Bjørn Solvang, Procedia Computer Science, 5th International Conference on Industry 4.0 and Smart Manufacturing, Accepted

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial Intelligence
AIMM	Autonomous Industrial Mobile Manipulation
AR	Augmented Reality
CAD	Computer-Aided Design
GAN	Generative Adversarial Networks
CNC	Computer Numerical Control
CNN	Convolutional Neural Network
CPS	Cyber-Physical System
IEC	International Electrotechnical Commission
IoT	Internet of Things
IIoT	Industrial Internet of Things
WPT	Wireless Power Transfer

1

Introduction

Manufacturers face a number of challenges that range from global competition to pandemics and lockdown. To stay competitive, manufacturers need to manufacture goods at a low cost while being able to adapt to market changes and consumers' needs [1]. In other words, the manufacturing industry is moving from mass production towards mass customization or personalized production. The transition to mass customization has numerous advantages but is challenging to implement [2]. Moreover, the pandemic has added another challenge to the manufacturers. Since the Covid-19 pandemic, the number of workers in factories and production systems has decreased. A consequence has been a delay in production and suspension of manufacturing lines. As a result, there is a need for a manufacturing system that is highly autonomous and can produce a wide variety of products.

Manufacturing systems have passed through three main paradigms, these being dedicated manufacturing system (DMS), flexible manufacturing system (FMS), and reconfigurable manufacturing system (RMS) [3], as shown in Fig. 1.1. DMSs are made with stationary and rigid machines, which are not flexible and are made to manufacture only one product at a time. These systems often use transfer lines [1] to manufacture a high volume of parts. Their production is efficient and has a low per-part cost. On the contrary, FMS are made to manufacture a large variety of products and consist of CNC or turning-type machines.

1. A transfer line is a manufacturing system with a predetermined line of machines to manufacture parts

Compared to DMS, FMS is a slower production process, and the per-part cost is higher [1].

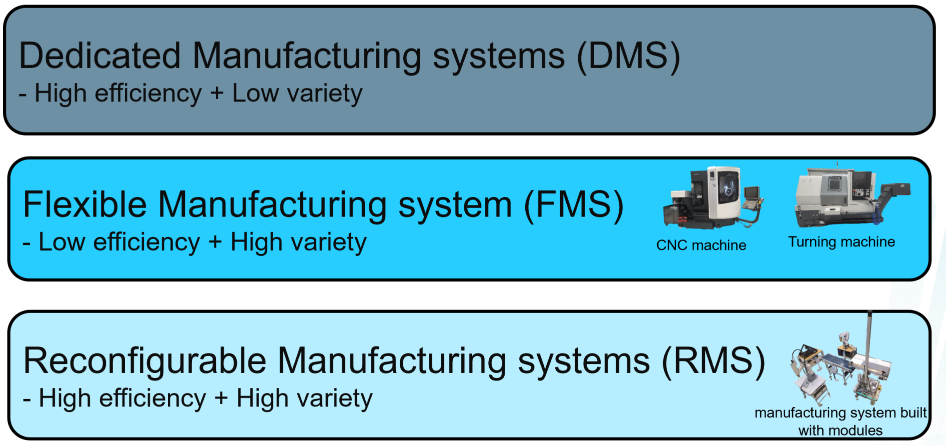

Figure 1.1: The three manufacturing paradigms.

The third paradigm, namely RMS, was proposed by Koren et al. [4] in the late 1990s and introduced modularity to manufacturing systems. RMS can be described as a modular manufacturing system where the system is made to be reconfigured. An RMS is made for fast reconfiguration on both the hardware and software level to adapt to changes in the market [5]. The main function of RMS is to be able to adjust the manufacturing systems depending on market needs [6]. A key objective of RMS is to manufacture a wide variety of products at a low cost. RMS combines the merits of efficient and fast manufacturing of DMS and combines them with the flexibility of FMS. It has been found that the lifetime[2] of RMS is three times longer than with DMS [7]. Moreover, switching from DMS to RMS had considerable capacity savings. The use of reconfigurable setups also resulted in a capacity reduction of around 50% over a seven-year period [8].

1.1 Challenges with RMS

There are however challenges with RMS. Traditional manufacturing systems such as DMS and FMS are often considered as being static (i.e., machines and equipment are rigid), while RMS is made to be modular where it is possible to reconfigure the system.

2. System or machine lifetime is the total number of years the system or machine will operate after it has been commissioned.

1.1.1 Practical/physical implementation of RMS

With RMS, there is a lack of physical implementation and demonstrations. Khanna et al. [9] did a review on RMS and found that implementing RMS is still a major challenge. They also noted that further research should focus on efficient methods for designing RMS, but should also consider its practical side. Pansare et al. [10] found that there is a lack of examples of successful implementation of RMS practices. In a literature review on the future direction of RMS, Singh et al. [11] mention that there is a need for more research on the development of reconfigurable machines. In another literature review, Morgan et al. [12] note that further research should look at how to retrofit the current manufacturing machine with virtualization and CPS architecture. They suggest developing a system that can autonomously change and have the intelligence to know how to change the system. There is also a lack of research on self-configuration, scalability, and interoperability. Isabela et al. [13] looked at the barriers to implementing RMS and found multiple challenges such as lack of modular equipment, lack of reconfiguration of controller architecture, difficulty in integrating new components and technologies, and difficulty in adding and removing equipment within the system.

There are, however, some examples of physical RMS. Sanderson et al. [14] presented a smart manufacturing and reconfigurable technology demonstrator. The demonstrator is built with HAS-200 [15], which is a training system that is modularized. The modules can be set up with different configurations and can produce a total of 19 product recipes. Another example is from Kemeny et al. [16], who built a smart factory using FESTO Didactic modules. The system is also described as a scaled-down learning factory used in higher education. There are also multiple examples [17, 18, 19, 20] of RMS that use the standardized platform from the FESTOs CP factory [21]. The FESTO CP factory is a modular factory, which is used for both research and as a learning platform. Another example of an RMS learning platform is from Kim et al. [22]. They developed a modular testbed that included ten workstations that could be reconfigured to manufacture electric toothbrushes, electric endodontic handpieces and battery chargers. However, all of these systems are used in training, education, and research, and are not implemented in an industrial manufacturing system.

There are also examples of systems that are made for industrial cases. Adamietz et al. [23] developed an RMS inside a container. In the container, modules can be replaced, and a full reconfiguration can take less than 8 hours with a forklift. The system can be set up with a maximum of six small modules or a combination of small and large modules. However, to run the system, a human must move the parts between the modules. In the example, the container is set up with additive manufacturing (AM), CNC milling, assembly, cleaning, and sterilization modules. Radanovic et al. [24] developed a standardized modular platform that used a plug and produced connectors to connect platforms together. It allows users to disassemble platforms and rebuild robotic work cells by changing or moving the platforms. Kang et al. [25] created a modular manufacturing system that utilized additive manufacturing. In the system, modules can be added and removed and in the example, it includes a 3D printer, post-processing, assembly and packaging.

1.1.2 Design problems

The second research challenge with RMS is planning the rearrangement of an RMS. In a literature review on layout design for RMS, Maganha et al. [26] found that there is a need to create new methods to design a layout for RMS. There are examples of researchers who have worked on the layout problem for RMS, but their work mainly focuses on scheduling [27], cost optimization [28, 29, 30, 31], scalability planning [32], and process planning [33, 34]. However, there is a lack of research on the placement of the machines and how the system should be reconfigured. Sabioni et al. [35] revealed that most papers focused on minimizing costs when optimizing RMS configurations. However, they did not find examples of systems where both the machine configuration and layout design problem were considered at the same time.

Benderbal et al. [36] looked at the best placement of machines for an RMS. In a second study, Benderbal et al. [37] developed a decision support system that can assist with switching between products. Nevertheless, both studies investigated a system where the machines were placed in predefined locations.

1.1.3 Reprograming of RMS

Robots are becoming more common in manufacturing systems. The challenge with using robots in manufacturing is that they are typically employed to perform repetitive work, which offers little or no variety. Most robot applications in manufacturing systems today use fixed systems, where the robots repeat the same tasks [38]. There are a number of challenges with RMS due to its dynamic nature, where robots and other manufacturing machines can be moved and rearranged. This means that it can be difficult to automate such systems because robots and other machines have to be programmed for each reconfiguration.

Brecher et al. [39] mentioned that using the teach pendant of the robot arm to program the robot for each reconfiguration is not suitable since robot programming requires expertise and can be time-consuming. When the system is being reconfigured, the manufacturing needs to stop, which will lead to extra cost and loss of production [32]. This in turn means that a slow reconfiguration process leads to additional manufacturing costs.

1.1.4 RMS with Industry 4.0

To overcome the challenges with RMS, Industry 4.0 has been proposed as a solution [13, 40]. Industry 4.0 is the fourth industrial revolution for the manufacturing industry and was coined in Germany. The focus of Industry 4.0 is digitalized and networked production [41, 42]. Moreover, Industry 4.0 includes key technologies, with a focus on the development of smart factories [43]. There is no agreed list by researchers on what technologies are included. However, there are ten technologies that are frequently used in the context of Industry 4.0 and those are the internet of things (IoT), big data and analytics, artificial intelligence (AI), simulation and digital twin modeling, advanced robotics, additive manufacturing, cloud technology, virtual and augmented reality, blockchain, and cyber-physical systems (CPS) [44].

As there are ten key technologies in Industry 4.0, it is out of the scope of this research project to investigate and implement all of them. In this research project, additive manufacturing, advanced robotics, big data, digital twin and simulation, IIoT, and AI are investigated. Cloud computing will not be investigated as the focus of the research is on the machine floor level, and cloud computing can often be considered as a higher level of control or interaction with the system. Virtual and augmented reality are technologies that require human input. However, the goal of this research is to automate the system without requiring human intervention. Blockchain is not a technology that increases automation and CPS is not directly a technology and will therefore not be considered.

The following section discusses what has been done within RMS and additive manufacturing, advanced robotics, big data, digital twin and simulation, IIoT, and AI.

1.1.5 Additive manufacturing

A technology from Industry 4.0 that can help create a manufacturing system to produce a large variety of products is additive manufacturing. Additive manufacturing uses less materials, lowers carbon footprint by reducing transportation, and can reduce the need for inventories compared to traditional manufacturing methods [45]. In addition, additive manufacturing is a technique where a large range of products can be produced, allowing manufacturing companies to move towards mass customization and personalized production.

There are examples of including additive manufacturing in RMS [23, 46]. Kang et al. [25] used a 3D printer in an RMS and mentioned that a key advantage of 3D printing is that it offers the capability of achieving mass customization/personalization and smart manufacturing.

1.1.6 Advanced robotics

Advanced robotics has been studied for RMS. Gaspar et al. [47] developed a robot work cell where the goal is to automate low-volume manufacturing. The work cell consists of plug-and-produce connectors to quickly add modules, fast tool change for the robot arms, and a flexible Gough Stewart fixture to hold parts. In addition, some of the work cell reconfigurations had to be done manually, while others could be done automatically using robot arms.

Inoue et al. [48] proposed using mobile manipulators as an important part of RMS. They used the mobile manipulator as a flexible method to transfer parts between machines in the RMS. It is also mentioned that it is not feasible to have skilled engineers do the reconfiguration of the manufacturing system. Xu et al. [49] developed a reconfigurable modular robot arm that can change the tools of the robot arm and has an adaptive control system. The system is built with wireless communication and has neural adaptive control. Madsen et al. [17] used a mobile manipulator with the reconfigurable FESTOs CP factory. In the system, the mobile manipulator is used to feed parts into the manufacturing line.

1.1.7 Big data

Big data is the collection and processing of large amounts of data. The collected data can further be used to get insight into the manufacturing system and can be used with AI for failure predictions [44]. There are different fields within big data depending on the data. For example, data collected from machine controllers, manufacturing systems, and sensors can be categorized under industrial big data [50]. However, to the author's knowledge, there is no paper that investigates how big data or industrial big data can be used with RMS.

1.1.8 Digital twin and simulation

Digital twins and simulation are technologies that copy the physical world in a virtual environment and can be used to monitor and test a system in a virtual environment before being employed on a physical system [44]. Leng et al. [51] proposed using digital twins as a method for reducing the time required for production changeovers. Kurniadi et al. [52] used both discrete and visual simulation to show how digital twins can be used for reconfiguration planning. Yang et al. [53] proposed a framework for digital twin simulation applications into RMS. They used a discrete event digital twin for design, as an information model, and as an assessment model. Moreover, the system is applied to an automotive part manufacturer.

A review [54] on RMS digital twin framework found that the use of digital twins can increase the efficiency and intelligence of the system by providing functions such as simulation and intelligent sensing. Additionally, artificial intelligence can enhance the performance of the digital twin.

1.1.9 Internet of Things

IoT refers to network technology that connects physical objects such as cars, buildings, and sensors together [44]. Moreover, industrial IoT is the industrial version of IoT and refers to machine-to-machine and automation communication systems [55]. Regarding RMS, Nayak et al. [56] highlight the importance of flexible architecture for the information and communication technology in the system. In a literature review on state-of-the-art RMS, Morgan et al. [12] found that IoT can enable scalability, modality, extensibility, and interoperability in manufacturing devices.

Kurniadi et al. [57] proposed a framework for IoT and RMS and mentioned that IoT is being applied to RMS. It is noted that integrating IoT with RMS facilitates the integration and organization of machines, operators, and data. Meyer et al. [58] analyzed the gap in the standardization of IIoT technologies and noted that there is a need for new standards within IIoT to support the transition into flexible and reconfigurable production. Furthermore, Tang et al. [59] proposed a cloud-assisted manufacturing architecture for RMS that used IIoT as a bridge between devices and an intelligent production edge. Kang et al. [25] built a modular manufacturing system and proposed a system where 3D printers and other manufacturing processes can be controlled with IoT.

1.1.10 Artificial Intelligence

AI refers to methods that enable a system to mimic human thinking and rationality. It encompasses disciplines such as machine learning, computer vision, robotics, automated reasoning, and natural language processing [44]. It should be noted that AI is a broad term, and under AI, machine learning is included.

Machine learning is a method that uses algorithms to learn from data. It allows for creating systems without programming them manually [60]. Moreover, AI is also included in other Industry 4.0 technologies, such as advanced robotics and big data and analytics. However, there is a lack of research on the implementation and use of AI in RMS, and how AI can be used to create an intelligent and self-controlling RMS.

1.1.11 Summary

In conclusion, research has revealed several challenges facing Reconfigurable Manufacturing Systems (RMS). A notable concern is the limited investigation into the physical implementation of RMS. Furthermore, the majority of examples center around educational systems, with all instances relying on human intervention for reconfiguration—a costly and time-intensive process. Challenges also arise in planning a new layout for RMS. Past research has primarily concentrated on aspects such as scheduling, cost optimization, scalability planning, and process planning. However, there is a lack of attention given to the development of methodologies for determining the optimal placement of platforms. Additionally, post-reconfiguration adjustments and reprogramming of robots and machinery requires specialized expertise and consumes valuable time.

Industry 4.0 has been suggested as a potential solution to address these hurdles, leveraging additive manufacturing, advanced robotics, big data, digital twin and simulation, the Industrial Internet of Things (IIoT), and artificial intelligence to enhance RMS automation. However, the current body of research exploring the application of Industry 4.0 technologies in tackling these challenges remains insufficient.

1.2 Research questions and objectives

This chapter addresses the research questions and objectives.

1.2.1 Research questions

As mentioned in section 1.1.1, one of the challenges of RMS is the lack of physical or practical implementation. There exist examples of learning systems that can be reconfigured, but they are limited in the rearrangement of the platforms. Furthermore, there are fewer examples of modular platform-based RMS that can be quickly reconfigured. Additionally, all existing RMS implementations require human labor for reconfiguration. To the author's knowledge, there is no implementation of an RMS that can be automatically reconfigured. The first research question is:

How can a platform-based RMS be built with reduced reconfiguration time in comparison to existing research while also being automated in order to reduce the human workload in the reconfiguration process?

Further, in section 1.1.2 and 1.1.3, it is noted that planning a reconfiguration of the RMS and programming robots after the reconfiguration remains a challenge. Both processes are time-consuming and require expertise which can increase the manufacturing cost. Moreover, Industry 4.0 has been proposed to overcome the challenges of reconfiguration [13, 40]. However, there is still a lack of practical implementations on how the Industry 4.0 technologies can be implemented into RMS [61]. Therefore, the second research question is:

What is the impact of Industry 4.0 technologies, additive manufacturing, advanced robotics, big data, digital twin and simulation, IIoT, and AI on RMS, and how can these technologies be integrated into RMS to improve its performance and efficiency?

There are also challenges and research gaps in the design and reprogramming of RMS. In terms of design, there is a lack of research on optimizing machine placement and layout design for RMS, with most existing studies focusing on scheduling, cost optimization, scalability planning, and process planning. In terms of reprogramming, the dynamic nature of RMS makes it difficult to automate since robots and other machines have to be programmed for each reconfiguration, leading to extra costs and loss of production. The third research question is:

How can multiple Industry 4.0 technologies be utilized to develop an intelligent and self-RMS that can optimize machine placement and layout design for efficient and cost-effective reconfigurations while minimizing production downtime and the need for human expertise in programming?

1.2.2 Research objectives

Due to the absence of physical examples of how RMS looks and the dependence on human labor for reconfiguration in existing examples, the primary research objective is to construct a physical platform-based RMS that can be reconfigured automatically, without human intervention. In chapter 2, papers 1 and 2 propose a novel RMS that incorporates multiple manufacturing platforms which can be reconfigured using a mobile robot. Furthermore, the concept of a highly adaptable and flexible RMS is also introduced.

The second objective is to examine the impact of Industry 4.0 technologies on RMS. This investigation involves the integration of these technologies into the highly flexible RMS to assess how they can enhance its efficiency and performance. In Chapter 3, several papers are presented that explore the utilization of different Industry 4.0 technologies in RMS. Specifically, papers 2 and 3 discuss the use of additive manufacturing, while papers 1, 2, and 4 investigate the application of advanced robotics. Paper 5 explores the potential of industrial big data, paper 2 examines how digital twin and simulation can be leveraged for reconfiguration, and papers 2, 3, and 5 discuss the use of IIoT. Finally, papers 2 and 8 propose wireless power transfer as a solution for electrifying RMS and propose its integration as a component of the RMS system.

The third objective is to integrate multiple Industry 4.0 technologies to address the issues of layout design and reprogramming of RMS. In Chapter 4, paper 7 proposes a smart layout design system that employs digital twin, simulation, IIoT, and optimization techniques to automatically generate a new layout for the highly flexible RMS. Additionally, paper 8 presents an architecture for constructing and organizing an intelligent RMS, showcasing how such a system can be realized in a physical RMS.

1.3 Structure of thesis

The main body of the thesis is structured into five chapters. The chapters of the thesis and their connection to the papers can be seen in Fig. 1.2.

Chapter 1 defines the paradigm within the manufacturing industry. In addition, it discusses challenges associated with RMS and how Industry 4.0 technologies are being used with RMS. It then describes the research questions and structure of the thesis.

Chapter 2 proposes a different method to make autonomous industrial mobile manipulators (AIMM) more flexible and reconfigurable. Furthermore, it proposes and shows the concept of highly flexible RMS. In addition, the chapter demonstrates a state-of-the-art highly RMS that uses a mobile robot for automatic reconfiguration.

Chapter 3 shows how Industry 4.0 technologies i.e., IoT, big data and analytics, AI, digital twin and simulation, advanced robotics, and additive manufacturing can be added to an RMS. Moreover, Wireless power transfer (WPT) is proposed as an Industry 4.0 technology and demonstrates how it can be imple-

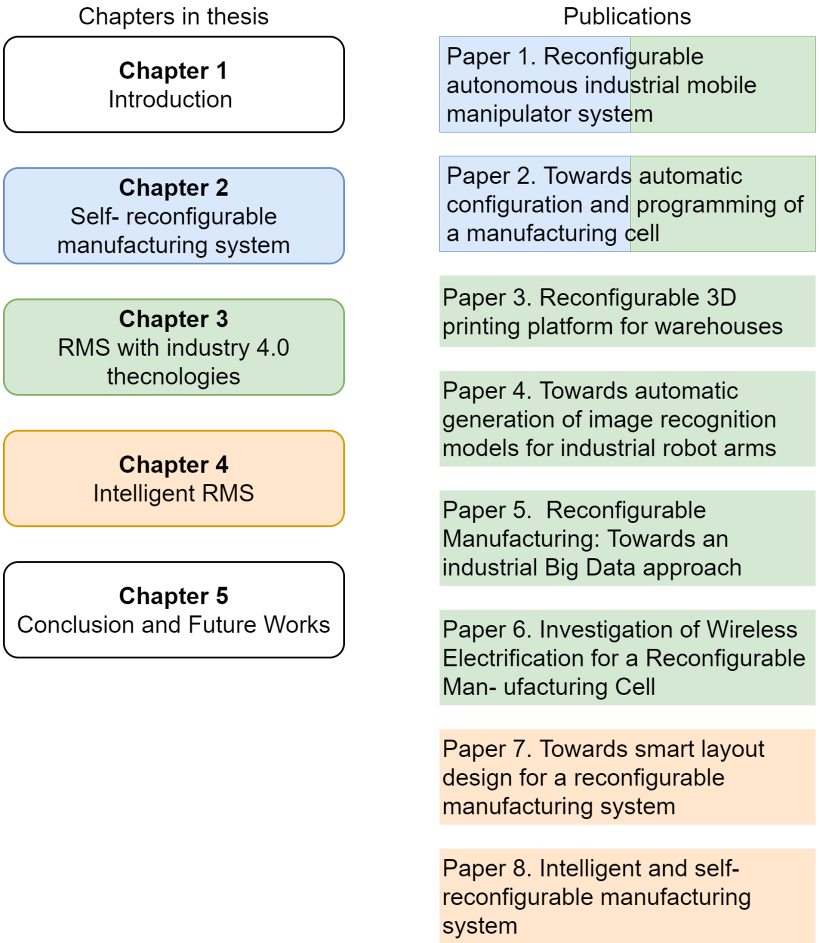

Figure 1.2: A color-coded connection between research papers and chapters in the thesis.

mented.

Chapter 4 investigates how an intelligent RMS can be built. First, a method is presented for solving and automating the layout problem by combining Industry 4.0 technologies. Next, the chapter proposes an architecture for intelligent RMS and shows how the programming and reconfiguration of RMS can be automated.

Chapter 5 concludes with the findings of the project and proposes further work and research to be carried out.

2

Self- reconfigurable manufacturing system

This chapter proposes a new method of how to make mobile manipulators more flexible. Furthermore, this chapter proposes the concept of highly flexible RMS and demonstrates how such a system can be built.

2.1 Divided AIMM

As mentioned in section 1.1.6, mobile manipulators have been proposed for RMS. In industrial cases, mobile manipulators are also known as autonomous industrial mobile manipulators (AIMM). AIMM is a flexible mobile assistant that can perform tasks in various workstations [62]. The idea of AIMM is that they can work around humans in an industrial environment and perform tasks such as transportation, pick and place, classification, process control and quality control [63]. The AIMM includes a robot arm on top of a mobile robot, where the robot arm can perform various tasks at different locations. However, such a system also has disadvantages. For example, if the mobile robot is driving, the robot arm cannot work, and if the robot arm is working, the mobile robot cannot drive. This results in significant downtime for both the mobile robot part and the robot arm. In addition, both the robot arm and the mobile robot are expensive manufacturing equipment.

To increase the flexibility and utilization of the AIMM, paper 1 proposes dividing the AIMM into two parts. The robot arm is placed on a trolley platform that can be moved/transported with a mobile robot. The idea is that the mobile robot can transport the robot arm where it is needed, thereby increasing the usability of both parts. Additionally, the paper shows how the system can be built. In the system, a mobile robot is equipped with a docking system, and two old robot arms are placed on platforms (trolleys) with new control computers. In front of each platform, a marker is placed that the mobile robot can use to position itself to pick up the platforms, as shown in Fig. 2.1.

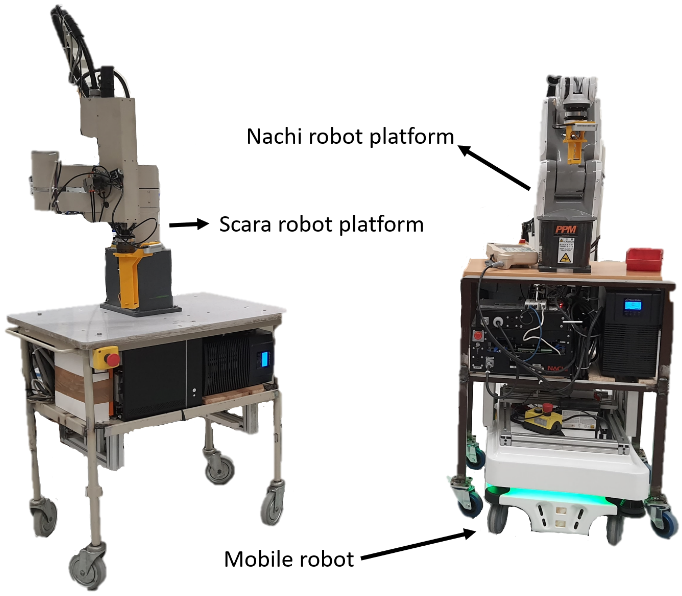

Figure 2.1: The two robot platforms and the mobile robot used for moving the platforms.

To show how the system works, a video is created `https://youtu.be/8gyoRbaeshk`. In the video, the mobile robot can pick up both robot platforms and place them at different workstations. Moreover, when the mobile robot is done moving the robot arms, it can do other logistics tasks. This is to showcase how the utilization of the mobile robot and robot arms can be increased by dividing them into separate systems that can also work together. In addition, the demonstrator shows how a mobile robot can be used to reconfigure the robot arm's platforms to various locations without the need for human intervention.

This paper advances the existing concept of AIMM, recognized for its flexibility and reconfigurability, by proposing a divided AIMM that exhibits even greater flexibility and reconfigurability than before.

However, a challenge with this system is that the mobile robot can only pick up the robot platforms at specific workstations. This in turn limits the flexibility of the system.

2.2 RMS with five platforms

There have been studies on RMS in containers [23], circular RMS where modules can be changed [25], and using the Feste CP factory [17, 18, 19, 20]. However, these systems suffer from slow reconfiguration. For example, a full reconfiguration for the RMS in the container takes up to eight hours and requires human labor [23].

A different idea is to expand the system in paper 1 to include other manufacturing equipment. A mobile robot can then move and reconfigure manufacturing platforms without any human intervention. To the author's knowledge, there are no publications that explore the use of mobile robots to rearrange machines in manufacturing cells. In paper 2, the idea of dividing the AIMM into two parts was expanded, and the concept of highly flexible RMS was created.

The concept of highly flexible RMS uses a mobile robot that can automatically move manufacturing platforms, such as robot arms, conveyors, 3D printers, etc. The mobile robot can automatically move the platforms and rearrange the RMS without human intervention. It should be noted that it is not possible for the mobile robot to reconfigure large manufacturing machines, such as CNC or turning centers. However, the mobile robot can still reconfigure platforms around these machines to create a manufacturing line.

Additionally, there is a notable scarcity of practical RMS implementations within the current literature, as indicated by Khanna [9] and Pansare [10]. Singh et al. [11] have identified a need for increased research into the development of reconfigurable machines. Furthermore, Morgan et al. [12] highlight the necessity for future research to explore strategies for retrofitting existing manufacturing machinery.

Therefore, to demonstrate how such a system works, a physical system was built, which includes five platforms:

- Nachi robot arm (six-axis)
- Scara robot arm (four-axis)
- 3D printer platform

- Conveyor platform
- Conveyor lift platform

All of the platforms in the system have been retrofitted with small computers, sensors, and state-of-the-art software for control. The idea is to showcase that old and outdated robots or other manufacturing equipment can be upgraded by adding new computers and software. This is an effective method of implementing industry 4.0 technologies such as IoT, digital twins, and AI into old manufacturing equipment.

The challenge with paper 1 is that the platforms could only be picked up and delivered to specific points in the laboratory. To make the system more flexible, a marker used for positioning was added to each of the platforms and could be lifted up and down. This allows the mobile robot to pick up the platforms in any location in the laboratory and move them to where they need to be. A video showcasing the docking and undocking of the platforms can be found at: `https://youtu.be/RtOXOHGiqRs`.

To show how the system works, a video demonstration is created `https://youtu.be/UXUlaawd8Ps`. The video starts with all the platforms having been spread around. Then the mobile robot picks up all the platforms and reconfigures a manufacturing line. Next, the system is taken apart and reconfigured around the virtual storage machine in the laboratory. The different layouts created in the demonstration can be seen in Fig. 2.2.

The idea is to showcase how a mobile robot can automatically reconfigure one manufacturing line, and then, after a production run is done, configure a new manufacturing line. A full reconfiguration of all five platforms in the system took about 12-14 minutes. This process is significantly faster compared to the container RMS [23], which requires up to eight hours for reconfiguration, or the Fasto CP factory which needs 1.4 hours [64].

Traditional fixed manufacturing systems, such as DMS and FMS, pose challenges in terms of modification and can be costly to alter. Furthermore, developing new manufacturing lines can be time-consuming and labor-intensive. The proposed system aims to address these issues by modularizing manufacturing machines, which simplifies the reconfiguration process. This approach enables a more efficient and rapid method for altering manufacturing lines. Additionally, a modular manufacturing system promotes the reusability of modules, preventing the need to discard the entire system each time a new part is produced.

Despite the advantages, the system does have some limitations. For example,

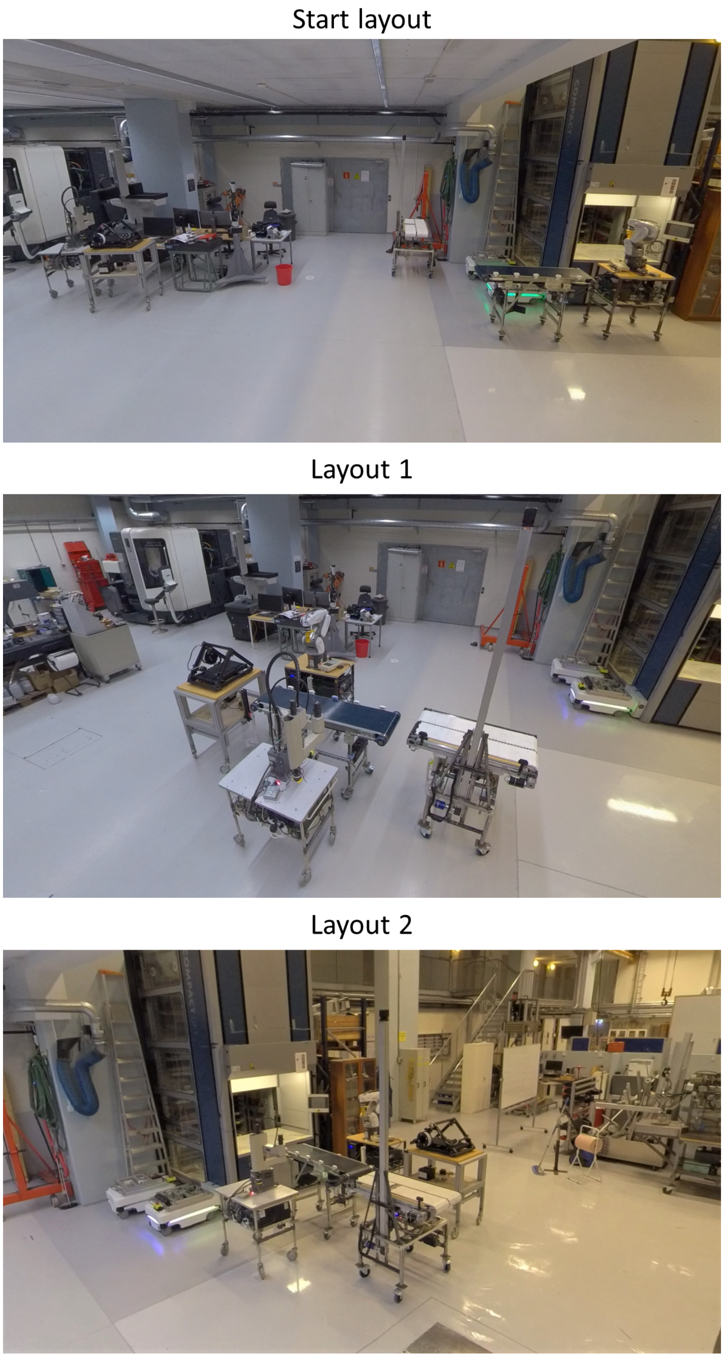

Figure 2.2: Start layout is the starting point, layout 1 is the first reconfiguration with the mobile robot, and layout 2 is the second reconfiguration with the mobile robot.

the mobile robot's accuracy is not optimal, potentially leading to misplacement of platforms. Additionally, when the mobile robot moves the platforms, it requires extra force. This force can cause one of its wheels to spin, which may significantly reduce its positioning accuracy. A potential solution to this problem could be to remove the wheels from the platforms, allowing the mobile robot to lift them instead. This would reduce the reliance on force and might improve the overall accuracy of the system.

3

RMS with industry 4.0 thecnologies

This chapter looks at how different Industry 4.0 technologies can be implemented into an RMS and how these technologies can be implemented in a physical RMS. The following Industry 4.0 technologies have been investigated and implemented; additive manufacturing, advanced robotics, Industrial big data, digital twin, simulation, and IIoT. In addition, WPT is suggested as a solution to electrify the RMS and is proposed as an Industry 4.0 technology.

3.1 Additive manufacturing

Several studies have examined how to integrate 3D printing into RMS [23, 46]. However, Seok et al. [25] mention that research on 3D printing has also been largely focused on the printer itself or models that use 3D printers for limited applications. It is noted that further research should focus on the advanced 3D printing models that use IT devices to move towards mass customization and mass personalization. Furthermore, Isabela et al. [13] notes the absence of a control architecture for RMS, which poses an obstacle to the effective implementation of RMS.

The inclusion of additive manufacturing has been proposed as a vital component of RMS. In paper 2, additive manufacturing is included in the concept of the highly flexible RMS. Furthermore, paper 4 proposes a control architecture on how the 3D printer platform can be integrated with IT systems. The system can be used to manage the 3D printer remotely. Moreover, the control system is integrated into the 3D printer, where the platform contains a Creality CR-30 3D printer, which is a conveyor printer. It prints at a 45-degree angle and can automatically eject the parts from the 3D printer. The image of the 3D printer platform with the mobile robot can be seen in Fig. 3.1.

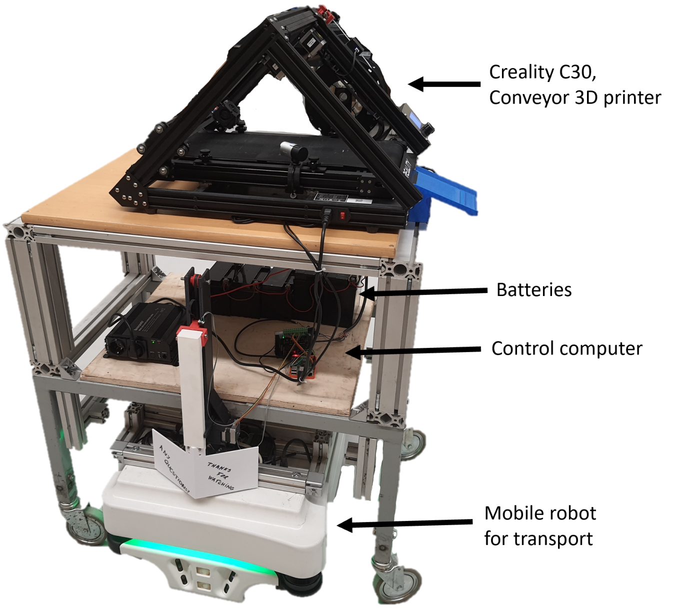

Figure 3.1: The 3D printing platform.

In paper 4, a movable 3D printing platform is proposed, that can be used to manufacture parts for warehouses. For example, being able to print parts at different locations in a warehouse to restock spare parts. Additionally, it is noted that an RMS can be used to replace large warehouses, where a highly flexible manufacturing system can produce the parts as they are needed instead of building large warehouses to store parts.

A demonstration video `https://youtu.be/Z6WQe1bf648` is made to showcase how the 3D printing platform can manufacture different parts at different locations. In the video, the 3D printer platform prints three parts in three locations. When the parts are printed, they are automatically ejected from the platform. The same system can be used to refill spare parts in a warehouse as they are running out.

From the experiments, the use of additive manufacturing with RMS creates an automated method of manufacturing a large number of parts. It is a flexible manufacturing technique that can enhance the RMS's mass customization capabilities.

It demonstrates the integration of 3D printers into RMS, illustrating their potential incorporation into a manufacturing system. However, the study has limitations. Future exploration is necessary to pinpoint which parts are best suited for printing. Additionally, the potential impact on the 3D printer's precision due to consistent transportation requires further exploration.

3.2 Advanced robotics and AI

Research has been conducted on enhancing the intelligence and adaptability of robots. However, there has been comparatively less emphasis on their integration into RMS. Moreover, extended programming and setup times for robot arms within an RMS can drastically augment the reconfiguration time of the system [39]. Additionally, there is a lack of studies and demonstrations on incorporating Industry 4.0 technologies, such as advanced robotics and AI, into RMS [61].

Papers 1 and 2 propose a novel approach on how platforms can be reconfigured automatically by using a mobile robot. However, using the mobile robot for reconfiguration creates challenges for the robot arms. When the mobile robot reconfigures the system, the platforms may not be accurately placed due to the mobile robot's low accuracy. This often results in misplacement of the platforms. This will create challenges for the robot arm platforms in the system since it is not possible to use pre-made robot programs. Moreover, it will also increase the reconfiguration time if the robot arm must be programmed for each configuration. It is necessary to make robot arms capable of locating objects in order to make them more flexible and adaptable to different environments.

In Paper 1, the robot arm platforms are equipped with 3D cameras, using a convolutional neural network (CNN) driven by AI to locate and identify objects. CNNs are feedforward neural networks capable of extracting features from images [65]. The camera with CNN can be used to control the robot arms and there is no need for high position accuracy from the mobile robot. A video demonstration showing how both robot arm platforms can pick up screws automatically can be found at `https://youtu.be/wvAcrwZMql0`.

However, using image recognition to control the robot arms presents challenges. Creating an image recognition model for each part requires multiple pictures and data labeling. This process is time-consuming, labor-intensive, and can increase manufacturing costs. However, often when manufacturing a new product, there is a 3D model of the product. In paper 5, a novel method to create image recognition models is proposed. The method uses a 3D model and from AI, a cycle generative adversarial network (GAN) to generate synthetic data, which can be used to train a CNN. The proposed method includes four main steps:

1. Generate images of the 3D model with different orientations.

2. Run these images through a cycle GAN to make them look more realistic.

3. Add background images and filters.

4. Train a CNN to recognize the parts.

When the image recognition model is created, it can be transferred to the robot arm to automatically pick-and-place objects. In the following video `https://youtu.be/5w34Q-QYKX8`, the image recognition model has been created from a 3D model and deployed on the robot arm.

By utilizing these methods to control the robot arms, an automated approach for manipulating the RMS can be achieved without the need for manual programming through a teach pendant. This streamlines the control process and enhances the efficiency and overall performance of the system. This system can further automate the reconfiguration of RMS and remove the need to program robot arms. However, there are still challenges with this system. In its current form, it only works reliably at close distances and struggles to identify objects further away.

This study has presented a method for increasing the automation of robot arms. Nevertheless, to make RMS a practical option that employs robots, additional methodologies are needed. These methods should aim to automate or simplify the programming and setup time of robots within the system.

3.3 Industrial big data

As mentioned in section 1.1.7, to the author's knowledge, there has been no investigation into using big data with RMS. Therefore, in paper 5, I investigated how industrial big data can be implemented into an RMS.

An RMS can consist of multiple platforms with machines and sensors. The data from these sensors and machines can be collected and used to build machine learning algorithms. For example, a machine learning algorithm can be built to predict when something will go wrong or when a certain situation has happened.

Paper 5 proposes an architecture on how to collect data from the platforms. A demonstration was conducted to showcase how industrial big data can be used in an RMS. The goal of the demonstration was to use the data from the mobile robot to predict which platform was being moved. To collect data from the system, the mobile robot drives to random points in the laboratory. A video showing how the data is collected can be found at `https://youtu.be/cX1r5Y_4Xfg`. When the data has been collected and sorted, an AI algorithm (K-nearest neighbors) is used to train a model to identify which platform is being moved using the data from the mobile robot.

Usually, industrial big data refers to large amounts of unstructured data and is not directly aimed at small manufacturing systems. However, the methods and tools in industrial big data are as applicable to smaller systems as they are to big systems. From the demonstration, paper 5 showed that it is possible to use the techniques from industrial big data with smaller amounts of data. Moreover, industrial big data, coupled with AI, can predict or classify problems or identify what is happening in the system.

Nonetheless, this study represents a single use case. Further exploration is required to understand how data can be utilized within an RMS to enhance automation. Additionally, determining which sensors should be incorporated into a modular RMS and identifying which data is valuable and relevant for RMS are essential areas for future investigation, as not all data may be significant.

3.4 Digital twin and simulation

Both digital twins and simulation are complementary technologies that have been noted as being important for RMS. Digital twins have previously been proposed as a tool to support the reconfiguration of RMS [51, 18] and Yang et al. [53] used a discrete event digital twin to evaluate the system. Despite these advancements, the bulk of prior research has been more intent on proposing frameworks and theoretical concepts. There is a lack of focus on the practical integration of a digital twin into the RMS and an investigation of how it can be employed to program and control the system.

Paper 2 proposes a novel method for programming a reconfiguration of the highly flexible RMS. The method uses a digital twin to plan where the platforms in the RMS should be placed. There is a digital twin of the environment, where the platforms in the RMS can be dragged to the desired positions. Then the digital twin can be used to simulate if the system works and if the robot arms can reach the required platforms. When the layout has been designed, the system sends the coordinates of the platforms from the digital twin to the mobile robot automatically for reconfiguration. This provides a simple and intuitive method to program and plan a new reconfiguration.

A video demonstration `https://youtu.be/vxsg4zgJzTU` was created to showcase how the system works. In the video, the digital twin is used to rearrange the platforms around a CNC machine. Then, a simulation is executed to check if the robot arms are able to reach the platforms and if the manufacturing line will work. When the simulation has been checked, the coordinates of the platforms are transferred to the mobile robot for automatic reconfiguration of the system. An illustration of the steps can be found in Fig. 3.2. This approach involves connecting a digital twin to the RMS and simplifying the programming of a new reconfiguration.

Additionally, simulation tools can be utilized to test potential RMS layouts prior to their physical implementation, leading to increased system efficiency. Nonetheless, as previously highlighted, the accuracy of the mobile robot is not that good, resulting in position deviations between the digital twin and the physical system's platforms. Therefore, an alternative method is needed to accurately track the positions of the platforms within the system.

3.5 IIoT systems

It has been noted that IIoT is a crucial part of RMS. However, its structure must be flexible to allow for reconfigurations [56]. Kang et al. [25] used IoT to control and monitor 3D printers and other machining processes. In their system, they used the protocol representational state transfer (REST). Tang et al. [59] proposed a network architecture where IIoT is used between the machines and the edge server. They used the Open Platform Communication Unified Architecture (OPC UA) standard for communication up to the edge. The OPC UA is an open-source International Electrotechnical Commission (IEC) communication standard often used for industrial systems. [66].

The previous research does not show how platforms or modules in an RMS can communicate or how machines interact with each other. Additionally, the lower lever control of the machines and how RMS platform can communicate and collaborate is ignored. Paper 1 proposed a control hierarchy for platforms in an RMS. The system proposes a method where the robot arm platforms can ask for transportation by a mobile robot or start processes from manufacturing

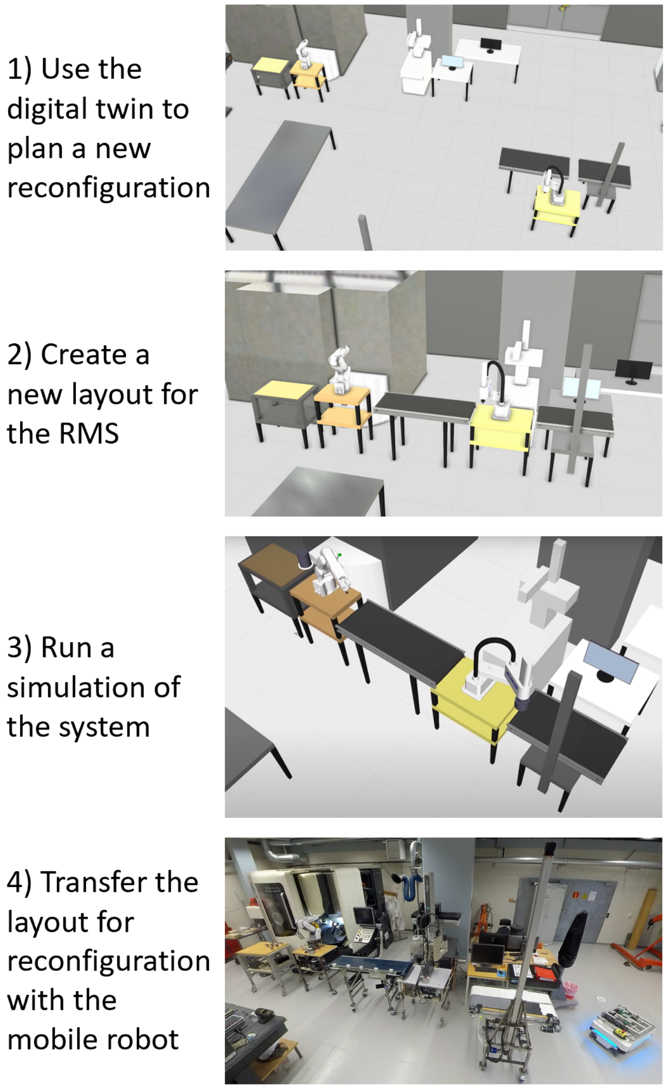

Figure 3.2: The four steps to plan a new layout for the RMS using the digital twin simulation.

machines. Moving control functions and decisions from the higher-level system can reduce the complexity of RMS.

In a literature review on state-of-the-art RMS, Morgan et al. [12] suggested that further research be conducted on retrofitting current manufacturing equipment. This can allow the old and outdated machines to be given new functionality, such as IIoT. Therefore, Paper 2 showed how old manufacturing machines could be retrofitted to modernize them. The platforms are fitted with new computers and sensors that wirelessly connect to an IIoT (OPC UA) server for monitoring and controlling the machines. Furthermore, paper 3 proposed an IIoT system that utilizes open-source software to control and monitor a 3D printing platform. The IIoT system can manage which part will be 3D printed and where the part is printed. Finally, paper 5 proposes an architecture on how data can be collected from the platforms in the RMS and how this data can be stored for further use in big data and analytics.

The OPC UA standard has been used extensively in papers 1-8. The OPC UA has given stable and simple-to-use communication between the platforms. Moreover, the OPC UA is often supported by manufacturing machines and software, including Visual Components, which is used as a digital twin and for simulation. Therefore, the OPC UA standard allows machine-to-machine communication and can be used to monitor and control the platforms. Moreover, connecting all platforms in a manufacturing cell allows centralized control of all computers and machines on the platforms.

In the studies, WiFi has been used for communication within the RMS. However, with the emergence of 5G technology, a more effective solution for communication may be possible. Balogh et al. [67] examined the use of a 5G cloud to control a mobile robot, noting that 5G was fast enough for real-time data transfer and control, and even discovered that it offered adequate speed for real-time data transmission and control. Future research should explore the utilization of 5G in RMS and conduct a comparative analysis of 5G and WiFi communication within RMS.

3.6 Wireless power transfer

One challenge with the highly flexible concept is how to electrify the platforms. All the platforms are equipped with batteries, which allows the system to operate for a fixed time before they need to be recharged. However, driving the platforms back and forward to get charged creates a lot of downtime for the platforms and system. Another solution would be to connect them to power after the system has been reconfigured. Nevertheless, manually connecting the platforms to power requires human labor and can result in cables around the manufacturing system.

Randanovic et al. [24] proposed standardizing connectors and plugs between platforms in an RMS. Another solution is to use a similar system used with mobile robots, where metal pins are used for power transfer. However, both these systems experience wear on the connection pins and the positioning of the platforms can become limited. Furthermore, to the best of the author's knowledge, there has been no exploration into the application of wireless power transfer (WPT) in electrifying manufacturing systems, or within RMS.

Paper 2 proposes to use WPT to electrify the platforms. By adding WPT connection points to the platforms, allows electricity to flow between the platforms to electrify the system. WPT is also proposed as an Industry 4.0 technology. Industry 4.0 is a dynamic concept, where the technologies included in Industry 4.0 change over time [42]. In addition, WPT and IoT are very similar in their function. The goal of IoT is to create wireless communication between devices, and WPT creates wireless electrification of machines. It can therefore be argued that WPT is an Industry 4.0 technology that can wirelessly electrify machines and other devices in manufacturing systems.

Paper 6 proposes a battery platform to increase the flexibility of the system. The highly flexible RMS is expanded to include a platform that only has batteries. The battery platform is used as a power bank to electrify the RMS. With such a system, there can be two battery platforms, one that is charging and a second battery platform that is powering the RMS. When the battery is running low, it can be replaced with the battery platform that is charging.

Furthermore, paper 6 demonstrates how to implement WPT into RMS with a battery platform. A simulation video `https://youtu.be/o3jhAhYdPUc` was created to demonstrate the functionality of the system. In the video, the mobile robot picks up a battery platform that was charging and then places it with the RMS. Then the mobile robot picked up the battery platform that was powering the RMS and placed it to be recharged. In addition, to showcase and prove the concept of using WPT and battery platforms for RMS, a physical demonstration was built. The RMS system was expanded, and a battery platform was added to the system. In the demonstration, the mobile robot picks up the battery platform and places it in front of the conveyor platform. Then, WPT from the battery platform to the conveyor is carried out to drive the conveyor. The video of the demonstration can be found at `https://youtu.be/KRwIdJ8fu5A`.

Nevertheless, the system and experiment present a limitation. For instance, the requirement of two metal plates on each platform can consume substantial space. While the study demonstrated powering a single platform with WPT, it did not extend to testing or exhibiting the powering of all modules in a manufacturing system. Moreover, significant misalignment could result in a considerable decrease in power transfer efficiency. Therefore, further research into the application of WPT for multiple platforms is needed, and research into the implications of misalignment and power efficiency.

4

Intelligent RMS

This chapter proposes a smart layout design system that aims to solve the layout design problem of RMS. Additionally, a framework for how to develop an intelligent self-RMS is proposed.

4.1 Smart layout design

RMS is designed to be reconfigured often. However, the challenge with such a system is that a new layout must be planned for each reconfiguration. Planning a new layout requires an expert in manufacturing, and it can be time-consuming work. Most of the previous research that addresses the layout design problem for RMS has focused on scheduling [27], cost optimization [28, 29, 30, 31], scalability planning [32], and process planning [33, 34]. Maganha et al. [26] highlight a need for models that aid in the design or redesign of new layouts for RMS.

Haddou Benderbal et al. [36, 37] utilized optimization to determine the optimal placement of machines. However, in these systems, the machines could only occupy fixed locations. Given the modularity of RMS and the objective to design a system where platforms have free mobility, ideally, the machines should have the flexibility to be positioned anywhere.

Paper 7 proposes a novel mathematical model that describes the highly flexible RMS in paper 2. It also combines IIoT, digital twin, simulation, advanced robotics, and AI to develop a smart layout design system. In the system, AI is used for optimization, namely evolutionary computations, to optimize the layout. The goal of the optimization is to design a layout that considers the limitations of the robot arms and finds the shortest path for the product to move in the system.

The input to the smart layout design system consists of the order of the platforms. The NSGA2 algorithm, combined with the mathematical model, is then used to search for a layout. A video showing the optimization with NSGA2 running can be found at `https://youtu.be/UNsugB0i4cs`. The layout is then transferred to the digital twin simulation, where the layout is tested to check for any collisions and if the layout will work. After the validation, the layout is sent to the mobile robot with IIoT to reconfigure the system automatically. Fig. 4.2 illustrates how the system works.

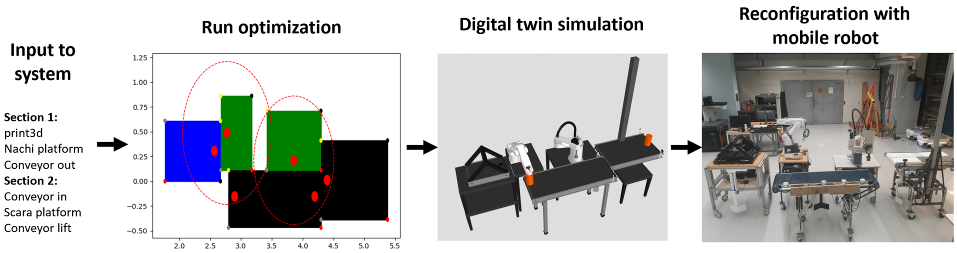

Figure 4.1: Illustration of how the smart layout design system works.

The smart layout system is tested with various numbers of platforms and on a physical system. The results of the optimization and digital twin solution can be found in table 4.1.

Table 4.1: The table lists the tests conducted with the smart layout systems.

System	Link
Layout 1 (three platforms, simplest form)	`https://youtu.be/YVbpl2U_L8I`
Layout 2 (seven platforms in one line)	`https://youtu.be/MTCSDvy0Qag`
Layout 3 (two sections)	`https://youtu.be/gZxg1X57g3Y`
Layout 4 (big system)	`https://youtu.be/GFiIdPl_0_E`
Test on a physical system	`https://youtu.be/TqimTSBvpTs`

By utilizing a smart layout design system for RMS, the planning of a new layout can be automated, eliminating the need for an operator to handle the task manually. This, in turn, enhances the efficiency of the RMS. However, as shown in the results, the system is not able to find the shortest path. In addition, the optimization time increases exponentially with the number of platforms in the system. For example, it takes around 1.3 days to optimize with 25 platforms. There is a need for further improvements in the optimization method. For instance, improvements might be achieved by using reinforcement learning or by combining reinforcement learning with different types of evolutionary computation to increase both the optimization speed and the quality of the results. Furthermore, more constraints should be added to the mathematical model, where it automatically finds the number of machines required for a given demand.

4.2 Intelligent self-RMS

As mentioned in section 1.1.3, rearranging the RMS requires re-programming the systems, which can be time-consuming and requires an expert to program the machines. One method to automate the reconfiguration of RMS is to combine multiple Industry 4.0 technologies into one system. However, previous research has shown that there is a need for an architecture or framework for smarter and reconfigurable machines [12]. Moreover, Sahoo et al. [68] noted that there is a lack of knowledge on how to implement smart manufacturing. In addition, to the author's knowledge, there is no publication that proposes an architecture or method that automates the reconfiguration process.

Therefore, paper 8 proposes a novel architecture for building an intelligent RMS. The architecture consists of three main parts; the control computer, the edge server, and the platforms. The control computer is used to perform heavy computational tasks such as planning a new layout or training deep neural networks. In addition, the control computer is also used to send tasks to the platforms and tell them what to do. The edge server hosts the communication server for the computers in the RMS and stores the data from the system in SQL format. Each platform contains intelligent methods for control and monitoring. For this architecture, the following platforms are considered: a robot platform, a 3D print platform, and a conveyor platform. However, more types of platforms with similar functionalities can be added to the architecture. The robot arms are controlled with image recognition models, which can be generated automatically from CAD 3D models and transferred to the robot arms. Moreover, digital twins and simulation should be used to support the control of the robot arms. To monitor the platforms cameras and sensors are used, along with image recognition and machine learning, to detect abnormalities or any issues that may arise.

In addition to the intelligent architecture for RMS, the smart layout system (paper 7) is also included. By combining these two systems, we get a six-step process for reconfiguring the system, as shown in Fig. 4.2. First, a CAD 3D model or assembly model is set as input to the system. The second step is to generate or create a list of the platforms that are required to manufacture the part. From the list of platforms, a layout is created and optimized using AI, specifically evolutionary computations. The layout is validated in a digital twin simulation to check if the system will work or if there are any collisions between the platforms. After the validation, the coordinates of the platforms are then sent to the mobile robot for configuration of the RMS. The last step is to run automatic control of the system.

As previously highlighted, there exists a dearth of studies demonstrating practical implementation of RMS [9]. Moreover, Bortolini et al. [61] underscore the lack of research on the integration of Industry 4.0 technologies into RMS. Addressing this gap, Paper 8 presents and demonstrates how various Industry 4.0 technologies can be successfully implemented and function within an RMS.

To showcase how an intelligent RMS can work, video demonstrations are built. The first video demonstration `https://youtu.be/SwDNChz57ts` shows how the layout is generated, and the second video `https://youtu.be/Su7A_6GuF0s` shows the system being programmed and controlled automatically.

This work can be seen as the first step towards implementing intelligent RMS. There is a need for more practical implementation and demonstrations of intelligent RMS. The proposed architecture can be expanded to include higher-level systems and more types of platforms.

The study has limitations. The basic demonstration of two boxes might not reflect real-world complexities, and the slow operation speed of the robots and conveyors raises efficacy concerns for faster scenarios. While the system's error detection is focused on a specific 3D printer and robot arms, broader research is needed to explore diverse sensor data applications and the integration of various machinery. Additionally, more investigations are needed into how AI techniques can be used to automate the RMS reconfiguration process.

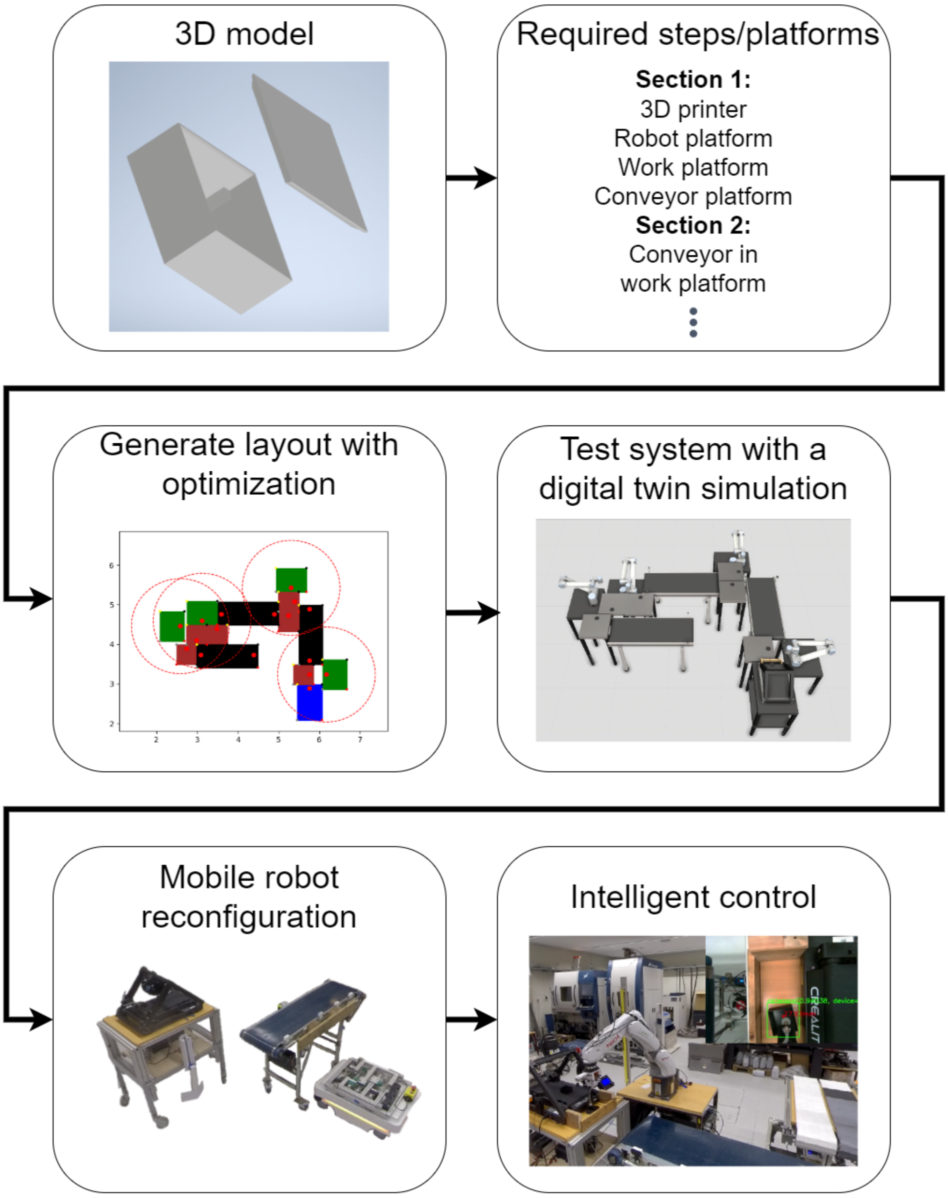

Figure 4.2: The six steps used for the intelligent RMS, when manufacturing a new product.

5

Conclusion

In research, there is a lack of practical implementations and examples of RMS. Moreover, all previous research has used human labor for the reconfiguration of the RMS. In this research, the use of mobile robots for reconfiguration in RMS has been explored. The concept of dividing an AIMM into separate parts was proposed to increase flexibility and utilization of the system. This concept was further expanded to develop a highly flexible RMS where a mobile robot can automatically move and rearrange manufacturing platforms without human intervention. A physical system was built to demonstrate how to build such a system and show the concept. Although there are limitations to the system, such as the mobile robot's accuracy and the need for extra force when moving platforms, the research shows promise for the development of automated methods for reconfiguration of RMS.

The second part investigates the potential impact of Industry 4.0 technologies on reconfigurable manufacturing systems (RMS). The highly flexible RMS was utilized to implement and study the integration of Industry 4.0 technologies. The research explored various technologies, including additive manufacturing, advanced robotics, industrial big data, digital twin and simulation, IIoT, and AI. Additive manufacturing was investigated as a means of automating the production of a diverse range of products in RMS. Advanced robotics with intelligent control were also explored for moving and handling parts in manufacturing processes. Industrial big data was investigated as a tool for analyzing and utilizing data collected from the RMS. Digital twins and simulation were employed as planning tools to test and validate new layout configurations in a virtual environment. Machine-to-machine communication between platforms and control of the system were explored through IIoT. AI is a tool to enable intelligent control and monitoring of the RMS, which can enable a higher level of automation. In addition, wireless power transfer (WPT) was proposed as a potential solution for wirelessly electrifying RMS and was suggested to be a part of Industry 4.0. The research shows the benefits of integrating Industry 4.0 technologies into RMS, which could lead to more efficient and automated manufacturing processes.

The reconfiguration of RMS can be a time-consuming and complex task. Previous research has mainly focused on scheduling, cost optimization, scalability planning, and process planning. However, there is a lack of investigation into optimization for machine placement in an RMS. To address this, A mathematical model and a smart layout design system is proposed that utilizes Industry 4.0 technologies such as IIoT, digital twin, simulation, advanced robotics, and AI to optimize the layout of RMS. The smart layout design system is tested on different amounts of platforms and a physical system.

Furthermore, a novel framework for an intelligent RMS that automates the reconfiguration process is proposed. The framework demonstrates how to develop an intelligent RMS which can be programmed automatically. The framework for intelligent RMS is combined with the smart layout design system to fully automate the reconfiguration process. Overall, these works represent significant contributions toward the automation and optimization of RMS.

5.1 Future works

As RMS is a relatively new manufacturing paradigm, there are still many challenges.

- In the project, a state-of-the-art RMS is built to showcase how an RMS can work. However, future research should investigate how to build platforms for RMS and how they can be implemented into a manufacturing system. Further research is needed to enhance the mobile robot's accuracy in platform positioning.

- More investigation into how additive manufacturing can be implemented into an RMS should be carried out. This might show how a large number of 3D printers can be implemented and how metal additive manufacturing can be used in RMS, to move towards mass customization.

- More investigation into methods, and what data can be extracted from an RMS, to make predictions and improve the system.

- The smart layout system can be expanded to consider more elements of the optimization.

- There is also a lack of examples and methods on how to build intelligent/smart RMS. More investigation on what AI methods can be applied and how these methods can be combined to further enhance the RMS.

Bibliography

[1] Y. Koren. "General RMS Characteristics. Comparison with Dedicated and Flexible Systems." In: *Reconfigurable Manufacturing Systems and Transformable Factories*. Ed. by Anatoli I. Dashchenko. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 27–45. ISBN: 978-3-540-29397-2. DOI: 10.1007/3-540-29397-3_3. URL: https://doi.org/10.1007/3-540-29397-3_3.

[2] Joanna Daaboul et al. "Design for mass customization: Product variety vs. process variety." In: *CIRP Annals* 60.1 (2011), pp. 169–174. ISSN: 0007-8506. DOI: https://doi.org/10.1016/j.cirp.2011.03.093. URL: https://www.sciencedirect.com/science/article/pii/S0007850611000941.

[3] M. Reza Abdi et al. "Introduction to the Book." In: *Integrated Reconfigurable Manufacturing Systems and Smart Value Chain: Sustainable Infrastructure for the Factory of the Future*. Cham: Springer International Publishing, 2018, pp. 1–13. ISBN: 978-3-319-76846-5. DOI: 10.1007/978-3-319-76846-5_1. URL: https://doi.org/10.1007/978-3-319-76846-5_1.

[4] Y. Koren et al. "Reconfigurable Manufacturing Systems." In: *CIRP Annals* 48.2 (1999), pp. 527–540. ISSN: 0007-8506. DOI: https://doi.org/10.1016/S0007-8506(07)63232-6. URL: https://www.sciencedirect.com/science/article/pii/S0007850607632326.

[5] Yoram Koren and Moshe Shpitalni. "Design of reconfigurable manufacturing systems." In: *Journal of Manufacturing Systems* 29.4 (2010), pp. 130–141. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2011.01.001. URL: https://www.sciencedirect.com/science/article/pii/S0278612511000021.

[6] Yoram Koren, Xi Gu, and Weihong Guo. "Reconfigurable manufacturing systems: Principles, design, and future trends." In: *Frontiers of Mechanical Engineering* 13 (Nov. 2017). DOI: 10.1007/s11465-018-0483-0.

[7] Y. Koren. "The Emergence of Reconfigurable Manufacturing Systems (RMSs)." In: *Reconfigurable Manufacturing Systems: From Design to Implementation*. Ed. by Lyes Benyoucef. Cham: Springer International Publishing, 2020, pp. 1–9. ISBN: 978-3-030-28782-5. DOI: 10.1007/978-3-030-28782-5_1. URL: https://doi.org/10.1007/978-3-030-28782-5_1.

[8] Ann-Louise Andersen, Thomas D. Brunoe, and Kjeld Nielsen. "Investigating the Potential in Reconfigurable Manufacturing: A Case-Study from Danish Industry." In: *Advances in Production Management Systems: Innovative Production Management Towards Sustainable Growth*. Ed. by Shigeki Umeda et al. Cham: Springer International Publishing, 2015, pp. 274–282.

[9] Kamal Khanna and Rakesh Kumar. "Reconfigurable manufacturing system: a state-of-the-art review." In: *BENCHMARKING-AN INTERNATIONAL JOURNAL*

26.8 (Oct. 2019), pp. 2608–2635. ISSN: 1463-5771. DOI: 10.1108/BIJ-05-2018-0140.

[10] Rajesh Pansare, Gunjan Yadav, and Madhukar R. Nagare. "Reconfigurable manufacturing system: a systematic review, meta-analysis and future research directions." In: *JOURNAL OF ENGINEERING DESIGN AND TECHNOLOGY* (). ISSN: 1726-0531. DOI: 10.1108/JEDT-05-2021-0231.

[11] Ashutosh Singh et al. "Reconfigurable manufacturing systems: journey and the road ahead." In: *INTERNATIONAL JOURNAL OF SYSTEM ASSURANCE ENGINEERING AND MANAGEMENT* 8.2, 2 (Nov. 2017), pp. 1849–1857. ISSN: 0975-6809. DOI: 10.1007/s13198-017-0610-z.

[12] Jeff Morgan et al. "Industry 4.0 smart reconfigurable manufacturing machines." In: *Journal of Manufacturing Systems* 59 (2021), pp. 481–506. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2021.03.001. URL: https://www.sciencedirect.com/science/article/pii/S027861252100056X.

[13] Isabela Maganha et al. "A Classification of the Barriers in the Implementation Process of Reconfigurability." In: *Towards Sustainable Customization: Bridging Smart Products and Manufacturing Systems*. Ed. by Ann-Louise Andersen et al. Cham: Springer International Publishing, 2022, pp. 88–95. ISBN: 978-3-030-90700-6.

[14] David Sanderson et al. "Smart Manufacturing and Reconfigurable Technologies: Towards an Integrated Environment for Evolvable Assembly Systems." In: *2016 IEEE 1st International Workshops on Foundations and Applications of Self* Systems (FAS*W)*. 2016, pp. 263–264. DOI: 10.1109/FAS-W.2016.61.

[15] SMC International Training. *SMC International Training – The didactic division of SMC Corporation*. [Online; accessed 6. Jan. 2023]. Jan. 2023. URL: https://www.smctraining.com.

[16] Zsolt Kemény et al. "The MTA SZTAKI Smart Factory: Platform for Research and Project-oriented Skill Development in Higher Education." In: *Procedia CIRP* 54 (2016). 6th CIRP Conference on Learning Factories, pp. 53–58. ISSN: 2212-8271. DOI: https://doi.org/10.1016/j.procir.2016.05.060. URL: https://www.sciencedirect.com/science/article/pii/S2212827116305169.

[17] Ole Madsen and Charles Møller. "The AAU Smart Production Laboratory for Teaching and Research in Emerging Digital Manufacturing Technologies." In: *Procedia Manufacturing* 9 (2017). 7th Conference on Learning Factories, CLF 2017, pp. 106–112. ISSN: 2351-9789. DOI: https://doi.org/10.1016/j.promfg.2017.04.036. URL: https://www.sciencedirect.com/science/article/pii/S2351978917301543.

[18] Catherine da Cunha et al. "Designing the Digital Twins of Reconfigurable Manufacturing Systems: application on a smart factory." In: *IFAC-PapersOnLine* 54.1 (2021). 17th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2021, pp. 874–879. ISSN: 2405-8963. DOI: https://doi.org/10.1016/j.ifacol.2021.08.103. URL: https://www.sciencedirect.com/science/article/pii/S2405896321008521.

[19] *IMS Centre Laboratories | Intelligent Manufacturing Systems (IMS) Centre*. [Online; accessed 6. Jan. 2023]. Jan. 2023. URL: https://www.uwindsor.ca/intelligent-manufacturing-systems/299/ims-centre-laboratories.

[20] Nicole Jäpel. *Industrie 4.0 Modellfabrik*. [Online; accessed 6. Jan. 2023]. Jan. 2023. URL: https://www.htw-dresden.de/hochschule/fakultaeten/

info-math/forschung/smart-production-systems/industrie-40-modellfabrik.

[21] *CP Factory – The Cyber-Physical Factory - CP Factory - Learning factories, CIM/FMS Systems - - Learning Systems - Festo Didactic*. [Online; accessed 6. Jan. 2023]. Jan. 2023. URL: https://www.festo.com/us/en/c/technical-education/learning-systems/factory-automation-and-industry-4-0/learning-factories-id_FDID_01_02_05/.

[22] Yun Geon Kim et al. "Multi-agent system and reinforcement learning approach for distributed intelligence in a flexible smart manufacturing system." In: *Journal of Manufacturing Systems* 57 (2020), pp. 440–450. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2020.11.004. URL: https://www.sciencedirect.com/science/article/pii/S0278612520301916.

[23] Raphael Adamietz et al. "Reconfigurable and transportable container-integrated production system." In: *Robotics and Computer-Integrated Manufacturing* 53 (2018), pp. 1–20. ISSN: 0736-5845. DOI: https://doi.org/10.1016/j.rcim.2018.02.008. URL: https://www.sciencedirect.com/science/article/pii/S0736584517301515.

[24] Primoz Radanovic et al. "Design of a Modular Robotic Workcell Platform Enabled by Plug & Produce Connectors." In: *2021 20th International Conference on Advanced Robotics (ICAR)*. 2021, pp. 304–309. DOI: 10.1109/ICAR53236.2021.9659345.

[25] Hyoung Seok Kang et al. "The FaaS system using additive manufacturing for personalized production." In: *RAPID PROTOTYPING JOURNAL* 24.9 (2018), pp. 1486–1499. ISSN: 1355-2546. DOI: 10.1108/RPJ-11-2016-0195.

[26] Isabela Maganha, Cristovao Silva, and Luis Miguel D. F. Ferreira. "The layout design in reconfigurable manufacturing systems: a literature review." In: *INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY* 105.1-4 (Nov. 2019), pp. 683–700. ISSN: 0268-3768. DOI: 10.1007/s00170-019-04190-3.

[27] Bensmaine Abderrahmane, Mohammed Dahane, and Lyes Benyoucef. "A new heuristic for integrated process planning and scheduling in reconfigurable manufacturing systems." In: *International Journal of Production Research* 52 (Dec. 2014), pp. 3583–3594. DOI: 10.1080/00207543.2013.878056.

[28] Lokesh Kumar Saxena and Promod Kumar Jain. "A model and optimisation approach for reconfigurable manufacturing system configuration design." In: *International Journal of Production Research* 50.12 (2012), pp. 3359–3381. DOI: 10.1080/00207543.2011.578161. eprint: https://doi.org/10.1080/00207543.2011.578161. URL: https://doi.org/10.1080/00207543.2011.578161.

[29] Abderrahmane Bensmaine, Mohammed Dahane, and Lyes Benyoucef. "A non-dominated sorting genetic algorithm based approach for optimal machines selection in reconfigurable manufacturing environment." In: *Computers & Industrial Engineering* 66.3 (2013). Special Issue: The International Conferences on Computers and Industrial Engineering (ICC&IEs) - series 41, pp. 519–524. ISSN: 0360-8352. DOI: https://doi.org/10.1016/j.cie.2012.09.008. URL: https://www.sciencedirect.com/science/article/pii/S0360835212002240.

[30] Shokraneh K. Moghaddam, Mahmoud Houshmand, and Omid Fatahi Valilai. "Configuration design in scalable reconfigurable manufacturing systems (RMS);

a case of single-product flow line (SPFL).” In: *International Journal of Production Research* 56.11 (2018), pp. 3932–3954. DOI: 10.1080/00207543.2017.1412531. eprint: https://doi.org/10.1080/00207543.2017.1412531. URL: https://doi.org/10.1080/00207543.2017.1412531.

[31] Shokraneh K. Moghaddam et al. “Configuration design of scalable reconfigurable manufacturing systems for part family.” In: *International Journal of Production Research* 58.10 (2020), pp. 2974–2996. DOI: 10.1080/00207543.2019.1620365. eprint: https://doi.org/10.1080/00207543.2019.1620365. URL: https://doi.org/10.1080/00207543.2019.1620365.

[32] Wencai Wang and Yoram Koren. “Scalability planning for reconfigurable manufacturing systems.” In: *Journal of Manufacturing Systems* 31.2 (2012), pp. 83–91. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2011.11.001. URL: https://www.sciencedirect.com/science/article/pii/S0278612511000999.

[33] A. Azab and H.A. ElMaraghy. “Mathematical Modeling for Reconfigurable Process Planning.” In: *CIRP Annals* 56.1 (2007), pp. 467–472. ISSN: 0007-8506. DOI: https://doi.org/10.1016/j.cirp.2007.05.112. URL: https://www.sciencedirect.com/science/article/pii/S0007850607001138.

[34] Anuch Chaube, Lyes Benyoucef, and Manoj Tiwari. “An adapted NSGA-2 algorithm based dynamic process plan generation for a reconfigurable manufacturing system.” In: *Journal of Intelligent Manufacturing* 23 (Aug. 2010), pp. 1–15. DOI: 10.1007/s10845-010-0453-9.

[35] Rachel Sabioni, Joanna Daaboul, and Julien Le Duigou. “Optimization of Reconfigurable Manufacturing Systems configuration: a literature review.” In: June 2020.

[36] Hichem Haddou Benderbal, Mohammed Dahane, and Lyes Benyoucef. “Exhaustive Search Based Heuristic for Solving Machine Layout Problem in Reconfigurable Manufacturing System Design.” In: *IFAC-PapersOnLine* 51.11 (2018). 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018, pp. 78–83. ISSN: 2405-8963. DOI: https://doi.org/10.1016/j.ifacol.2018.08.238. URL: https://www.sciencedirect.com/science/article/pii/S2405896318313624.

[37] Hichem Haddou Benderbal and Lyes Benyoucef. “Machine Layout Design Problem Under Product Family Evolution in Reconfigurable Manufacturing Environment: A Two-Phase Based-AMOSA Approach.” In: *The International Journal of Advanced Manufacturing Technology* 104 (Sept. 2019). DOI: 10.1007/s00170-019-03865-1.

[38] Jose Luis Outón et al. “Innovative Mobile Manipulator Solution for Modern Flexible Manufacturing Processes.” In: *Sensors* 19.24 (2019). ISSN: 1424-8220. DOI: 10.3390/s19245414. URL: https://www.mdpi.com/1424-8220/19/24/5414.

[39] Christian Brecher et al. “Simulation Framework for Virtual Robot Programming in Reconfigurable Production Systems.” In: *Procedia CIRP* 86 (2019). 7th CIRP Global Web Conference – Towards shifted production value stream patterns through inference of data, models, and technology (CIRPe 2019), pp. 98–103. ISSN: 2212-8271. DOI: https://doi.org/10.1016/j.procir.2020.01.045. URL: https://www.sciencedirect.com/science/article/pii/S2212827120300597.

[40] Ashutosh Singh, Piyush Gupta, and Mohammad Asjad. "Reconfigurable Manufacturing System (RMS): Accelerate Towards Industries 4.0." In: *SSRN Electronic Journal* (Jan. 2019). DOI: 10.2139/ssrn.3354485.

[41] Wahlster W. Kagermann H. and Helbig J. In: (Feb. 2023). [Online; accessed 13. Feb. 2023]. URL: https://www.din.de/resource/blob/76902/e8cac883f42bf28536e7e8165993f1fd/recommendations-for-implementing-industry-4-0-data.pdf.

[42] Cristina Orsolin Klingenberg, Marco Antonio Viana Borges, and Jose Antonio Valle Antunes Jr. "Industry 4.0 as a data-driven paradigm: a systematic literature review on technologies." In: *JOURNAL OF MANUFACTURING TECHNOLOGY MANAGEMENT* 32.3, SI (MAR 25 2021), 570–592. ISSN: 1741-038X. DOI: {10.1108/JMTM-09-2018-0325}.

[43] Anbesh Jamwal et al. "Industry 4.0 Technologies for Manufacturing Sustainability: A Systematic Review and Future Research Directions." In: *Applied Sciences* 11.12 (2021). ISSN: 2076-3417. DOI: 10.3390/app11125725. URL: https://www.mdpi.com/2076-3417/11/12/5725.

[44] Ting Zheng et al. "The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review." In: *International Journal of Production Research* 59.6 (2021), pp. 1922–1954. DOI: 10.1080/00207543.2020.1824085. eprint: https://doi.org/10.1080/00207543.2020.1824085. URL: https://doi.org/10.1080/00207543.2020.1824085.

[45] Simon Ford and Mélanie Despeisse. "Additive manufacturing and sustainability: an exploratory study of the advantages and challenges." In: *Journal of Cleaner Production* 137 (2016), pp. 1573–1587. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2016.04.150. URL: https://www.sciencedirect.com/science/article/pii/S0959652616304395.

[46] Steffen Scholz et al. "A modular flexible scalable and reconfigurable system for manufacturing of Microsystems based on additive manufacturing and e-printing." In: *Robotics and Computer-Integrated Manufacturing* 40 (2016), pp. 14–23. ISSN: 0736-5845. DOI: https://doi.org/10.1016/j.rcim.2015.12.006. URL: https://www.sciencedirect.com/science/article/pii/S0736584515301642.

[47] Timotej Gašpar et al. "Smart hardware integration with advanced robot programming technologies for efficient reconfiguration of robot workcells." In: *Robotics and Computer-Integrated Manufacturing* 66 (2020), p. 101979. ISSN: 0736-5845. DOI: https://doi.org/10.1016/j.rcim.2020.101979. URL: https://www.sciencedirect.com/science/article/pii/S0736584519306726.

[48] Shinichi Inoue et al. "High-Precision Mobile Robotic Manipulator for Reconfigurable Manufacturing Systems." In: *International Journal of Automation Technology* 15.5 (2021), pp. 651–660. DOI: 10.20965/ijat.2021.p0651.

[49] Wenfu Xu et al. "A wireless reconfigurable modular manipulator and its control system." In: *Mechatronics* 73 (2021), p. 102470. ISSN: 0957-4158. DOI: https://doi.org/10.1016/j.mechatronics.2020.102470. URL: https://www.sciencedirect.com/science/article/pii/S095741582030132X.

[50] Jay Lee, Hung-An Kao, and Shanhu Yang. "Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment." In: *Procedia CIRP* 16 (2014). Product Services Systems and Value Creation. Proceedings of the 6th CIRP Conference on Industrial Product-Service Systems, pp. 3–8. ISSN: 2212-8271.

DOI: https://doi.org/10.1016/j.procir.2014.02.001. URL: https://www.sciencedirect.com/science/article/pii/S2212827114000857.

[51] Jiewu Leng et al. “Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model.” In: *Robotics and Computer-Integrated Manufacturing* 63 (2020), p. 101895. ISSN: 0736-5845. DOI: https://doi.org/10.1016/j.rcim.2019.101895. URL: https://www.sciencedirect.com/science/article/pii/S073658451930167X.

[52] Kezia Amanda Kurniadi, Sangil Lee, and Kwangyeol Ryu. “Digital Twin Approach for Solving Reconfiguration Planning Problems in RMS.” In: *Advances in Production Management Systems. Smart Manufacturing for Industry 4.0*. Ed. by Ilkyeong Moon et al. Cham: Springer International Publishing, 2018, pp. 327–334. ISBN: 978-3-319-99707-0.

[53] Jinho Yang et al. “Digital Twin-Based Integrated Assessment of Flexible and Reconfigurable Automotive Part Production Lines.” In: *Machines* 10.2 (2022). ISSN: 2075-1702. DOI: 10.3390/machines10020075. URL: https://www.mdpi.com/2075-1702/10/2/75.

[54] Emna Hajjem et al. “Digital Twin Framework for Reconfigurable Manufacturing Systems: Challenges and Requirements.” In: *ADVANCES IN PRODUCTION MANAGEMENT SYSTEMS: ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE AND RESILIENT PRODUCTION SYSTEMS, APMS 2021, PT II*. Ed. by A Dolgui et al. Vol. 631. IFIP Advances in Information and Communication Technology. IFIP WG 5.7 International Conference on Advances in Production Management Systems (APMS), Nantes, FRANCE, SEP 05-09, 2021. IFIP Working Grp 5 7 Advances Prod Management Syst; IMT Atlantique, Campus Nantes; Centrale Nantes; Univ Nantes; Rennes Business Sch; Audecia Business Sch. 2021, pp. 553–562. ISBN: 978-3-030-85902-2; 978-3-030-85901-5. DOI: 10.1007/978-3-030-85902-2_59.

[55] Emiliano Sisinni et al. “Industrial Internet of Things: Challenges, Opportunities, and Directions.” In: *IEEE Transactions on Industrial Informatics* 14.11 (2018), pp. 4724–4734. DOI: 10.1109/TII.2018.2852491.

[56] Naresh Ganesh Nayak, Frank Dürr, and Kurt Rothermel. “Software-defined environment for reconfigurable manufacturing systems.” In: *2015 5th International Conference on the Internet of Things (IOT)*. 2015, pp. 122–129. DOI: 10.1109/IOT.2015.7356556.

[57] Kezia Amanda Kurniadi and Kwangyeol Ryu. “Development of IOT-based Reconfigurable Manufacturing System to solve Reconfiguration Planning Problem.” In: *Procedia Manufacturing* 11 (2017). 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017, 27-30 June 2017, Modena, Italy, pp. 965–972. ISSN: 2351-9789. DOI: https://doi.org/10.1016/j.promfg.2017.07.201. URL: https://www.sciencedirect.com/science/article/pii/S2351978917304092.

[58] Olga Meyer et al. “Industrial Internet of Things: covering standardization gaps for the next generation of reconfigurable production systems.” In: *2018 IEEE 16th International Conference on Industrial Informatics (INDIN)*. 2018, pp. 1039–1044. DOI: 10.1109/INDIN.2018.8472048.

[59] Hao Tang et al. “A Reconfigurable Method for Intelligent Manufacturing Based on Industrial Cloud and Edge Intelligence.” In: *IEEE Internet of Things Journal* 7.5 (2020), pp. 4248–4259. DOI: 10.1109/JIOT.2019.2950048.

[60] Tin-Chih Toly Chen and Yi-Chi Wang. “Artificial Intelligence in Manufacturing.” In: *Artificial Intelligence and Lean Manufacturing*. Cham: Springer International Publishing, 2022, pp. 13–35. ISBN: 978-3-031-04583-7. DOI: 10.1007/978-3-031-04583-7_2. URL: https://doi.org/10.1007/978-3-031-04583-7_2.

[61] Marco Bortolini, Francesco Gabriele Galizia, and Cristina Mora. “Reconfigurable manufacturing systems: Literature review and research trend.” In: *Journal of Manufacturing Systems* 49 (2018), pp. 93–106. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2018.09.005. URL: https://www.sciencedirect.com/science/article/pii/S0278612518303650.

[62] Mads Hvilshoj et al. “Autonomous industrial mobile manipulation (AIMM): past, present and future.” In: *INDUSTRIAL ROBOT-THE INTERNATIONAL JOURNAL OF ROBOTICS RESEARCH AND APPLICATION* 39.2 (2012), pp. 120–135. ISSN: 0143-991X. DOI: 10.1108/01439911211201582.

[63] Mads Hvilshoj and Simon Bøgh. “"Little Helper" - An Autonomous Industrial Mobile Manipulator Concept.” In: *International Journal of Advanced Robotic Systems* 8 (June 2011). DOI: 10.5772/10579.

[64] Aau Smart Production. *Reconfiguration of AAU Smart Production Lab*. [Online; accessed 16. Jun. 2023]. Jan. 2018. URL: https://www.youtube.com/watch?v=pX74QVfZ-6A.

[65] Zewen Li et al. “A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects.” In: *IEEE Transactions on Neural Networks and Learning Systems* 33.12 (2022), pp. 6999–7019. DOI: 10.1109/TNNLS.2021.3084827.

[66] *Brochures - OPC Foundation*. [Online; accessed 30. Dec. 2022]. Oct. 2022. URL: https://opcfoundation.org/resources/brochures.

[67] Marcell Balogh et al. “Cloud-Controlled Autonomous Mobile Robot Platform.” In: *2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. 2021, pp. 1–6. DOI: 10.1109/PIMRC50174.2021.9569730.

[68] Snehasis Sahoo and Cheng-Yao Lo. “Smart manufacturing powered by recent technological advancements: A review.” In: *Journal of Manufacturing Systems* 64 (2022), pp. 236–250. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2022.06.008. URL: https://www.sciencedirect.com/science/article/pii/S0278612522001042.

Paper 1

Reconfigurable autonomous industrial mobile manipulator system

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Author's Contribution

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

Reconfigurable autonomous industrial mobile manipulator system

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Abstract— **The manufacturing industry is moving from mass production towards more personalized products through mass customization. In order to adapt factories should be highly flexible and rapidly able to adjust their operations.**

The new technologies and concepts in industry 4.0 are important in the transition from mass- to flexible and personalized manufacturing systems. One such specific tool for increased flexibility is the introduction of an Autonomous Industrial Mobile Manipulator (AIMM). The AIMM provides mobility with its mobile part and increased flexibility and functionality with the robot arm. However, a disadvantage with AIMM systems is that when the mobile robot is moving the robot arm cannot work; when the robot arm is working, the mobile robot cannot drive. This creates downtime for both the mobile robot and the robot arm.

In this paper, we will look at how an AIMM can be divided into two parts for increased utilization of the mobile part and robot arm of the AIMM. Our approach is to physically divide the system into two parts, one with the mobile robot and a second with the robot arm on a trolley. In this case, the mobile robot can transport the robot arm, detach from the robot arm and perform other tasks while the robot arm is working at its new location.

I. Introduction

Industry 4.0 is often referred to as the fourth industrial revolution. It is a manufacturing philosophy that includes a wide area of concepts and new technologies, such as Human-Machine and Machine-Machine communication, Internet of Things (IoT), Enterprise Resource Planning (ERP), Cloud technologies, Big data and mobile systems [1]. The vision of Industry 4.0 is to create a smart factory with intelligent Cyber-Physical Systems (CPS) [2].

Businesses that implement and master technologies, such as advanced automation, virtualization and flexibilization, will gain a competitive advantage [3]. The technologies in Industry 4.0 allow production companies to go from mass production with limited customization towards mass personalized production [4]. Mass personalized customization can be a lucrative strategy that comes with many advantages. However, it does come with some challenges, such as increased complexity in the production system [5]. To achieve mass customized production, the production system in itself has to be adaptive and highly flexible.

Robots are often used to perform simple tasks, which again requires the least amount of sophisticated technology [6]. They are usually mounted to the ground (fixed autonomous), which limits the robot's reach and decreases flexibility. New applications are emerging that require industrial robots (IR) to access environments previously inaccessible [7], and there is an increasing demand for robots performing more complex tasks [6]. Such as assembly tasks that require the robot to make decisions based on a changing environment.

One tool towards increased flexibility and mass customization is the introduction of an Autonomous Industrial Mobile Manipulators (AIMM). AIMM is a flexible autonomous manufacturing assistant that can be used for different manufacturing tasks. The idea behind AIMM is to have a more flexible and varied automation solution. It can work beside people, be fully automatic and be able to perform work at different workstations [8]. It is a combination of different technologies and concepts working together, where the four abbreviations can be explained by the following [9]:

- **Autonomous:** The robot is able to perform tasks independently, with no human intervention.
- **Industrial:** Refers to where the robot is utilized.
- **Mobile:** The robot can map and move around an industrial environment through its localization.
- **Manipulator:** The robot can do mechanical work, such as move objects or change arrangements of parts.

The AIMM benefits from the mobile robot with increased flexibility and mobility, and gets the functionality from having a robot arm [10]. Most of the recent research projects have used a standard mobile robot or ROS-based mobile robot together with an industrial or collaborative robot [11][12]. There have been EU funded projects [13][14] on mobile manipulators, and so companies have started to produce AIMMs, for example: KUKA KMR iiwa [15], Fetch Fright [16], Omron MoMa [17], ER-FLEX [18] and Robotnik mobile manipulators [19].

AIMMs have been tested in real manufacturing system, but there are still challenges and the technology should mature before being implemented in large-scale manufacturing operations [20]. There is a need for further development of control methods for the AIMM system and standardization of its components [9]. It should be noted that industrial robot arms and mobile robots are expensive investments. Typically, a medium sized industrial robot cost 50k€, while a mobile robot cost around 30k€. A substantial investment for most small and medium sized companies.

In order to increase the utilization of both the robot and the carrier we suggest to split the AIMM into two physical parts, the mobile robot and an industrial robot arm mounted on a trolley. This paper look at such division, how to build, connect and control the respective units.

The paper is organized as follows: Section 2 will discuss a new conceptual approach to the AIMM; Section 3 describes an experimental setup, how it works, and how it is connected

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together; Section 4 gives a demonstration of the experimental system; while Section 5 presents a discussion based on the demonstration and a conclusion.

II. An alternative approach to AIMM

One of the disadvantages of AIMM is that the robot arm and mobile robot are fastened together. When the robot arm performs tasks, the mobile robot has to stand still and vice versa. It creates a large amount of downtime for both the mobile robot and the robot arm.

As mentioned, an AIMM can be divided into two parts: a mobile robot and robot arm. A different approach is splitting the AIMM into two physical parts, one with a mobile robot and a second part with a robot arm on a moveable trolley. An illustration of such an AIMM can be seen in figure 1.

Fig. 1. The three figures showcase how an AIMM can be divided into two parts but also work together

The mobile robot can transport the robot arm, then detach itself from it, and do other tasks while the robot arm is working. This allows the mobile robot and robot arm to work as one unit and work separately from each other. This can decrease the mobile robot and robot arm's downtime while maintaining the flexibility of an AIMM system.

The trolley can be equipped with different types of robot arms (SCARA or n-DOF IR) or other machines, depending on what work has to be done. It should be mentioned that most AIMMs today use collaborative robots, since they can work beside humans and are not as dangerous as standard industrial robots.

Depending on the use of the system, it is possible to have multiple trolleys with robot arms and only one mobile robot to transport the robot arm to where it is needed. This again increases the flexibility of the production systems and cuts costs, since only a few mobile robots are required in order to transport the robots.

III. AIMM system structure

A proof of concept has been developed to demonstrate how an AIMM can be divided and how such system can work. In this chapter we will describe each key-component, its setup and connection to an industrial information server.

A. *Mobile robot system*

The first part of the system is the mobile robot. In this system we used the MiR100, which is a highly flexible autonomous mobile robot. It has a carrying capacity of 100kg and can pull up to 300kg [21].

There are two methods by which the mobile robot can move or transport the robot trolley, either through a hook system where the mobile robot latches onto the trolley and pulls it, or a system where the mobile robot drives under the trolley and then docks into the trolley. It is not recommended to pull the trolley (from outside), since it is harder for the mobile robot to move in a strict predictable way. Attaching the mobile robot under the trolley simplifies the movement of the unit.

The mobile robot is made to be flexible and it is possible to change or add a top-module. A simple top module, which uses a motor to move two L-formed pins outwards, has been developed, as can be seen in figure 2. When the mobile robot drives under the trolley, the two pins move outwards, which hooks the mobile robot to the trolley.

The positioning accuracy of the mobile robot is only ± 50 mm [21] and is too low to dock into a trolley reliably. However, the mobile robot is fitted with two 3D cameras in the front, which can be used for accurate positioning within ± 10 mm. This is done with either a V marker or a VL marker, which can be 3D printed and placed around a production environment for accurate docking positions, as shown in figure 2.

Fig. 2. The figure showcases both robot trolleys, the mobile robot with the pin system, and the marker used for docking with the mobile robot.

It should be noted that in this system the mobile robot can only pick up the robot trolley where there is a marker. Being able to pick up and place the robot in any position in the laboratory would further increase the flexibility of the system. However, that requires a different method to improve the accuracy of the mobile robot.

B. *Robot arm system*

There are two robot arms in this system, one SCARA Adept 604 (4-DOF) and a Nachi MZ07 (6-DOF). Both robot arms are placed on a movable trolleys, as shown in figure 2. Each trolley is equipped with an Uninterruptible Power Supply (UPS) to power the robots, controllers and grippers. Both robots are fitted with a 3D camera (Intel Realsense D435) used to identify, pick and place objects. The 3D cameras are fitted to the gripper on the robot arm, as shown in figure 3.

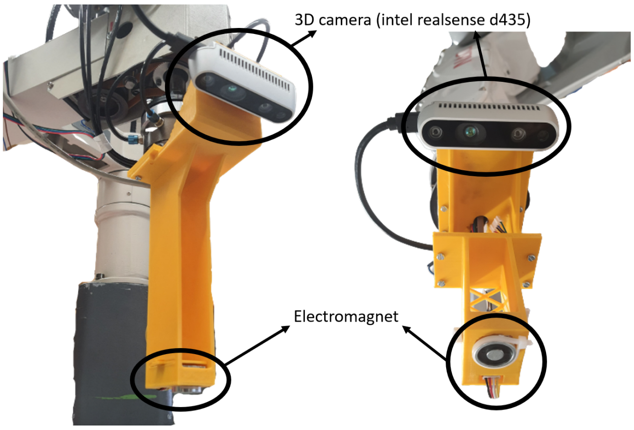

Fig. 3. The robot gripper for the Nachi and Scara robot

An open-source library OpenCV [22] was used for classification of objects. OpenCV is a computer vision and machine learning library that can be used for real-time vision applications [23]. When the robot gets a task to pick a specific item, it drives automatically out with a fixed routine to see if it can find the object using OpenCV. If the object is found the robot will position itself so that the object is in the middle of the camera view. When the robot has positioned itself, the 3D camera is used to read how far away the object is and the robot moves down to pick the object. An electromagnet is used to grip the object, as can be seen in figure 3. The electromagnetic gripper has been made to be flexible and does not require high accuracy where small objects will automatically get pulled towards the gripper.

C. IoT system

AIMMs are usually made to work remotely and wireless, and should be able to communicate with other machines as well as human operators [24]. In our previous project [25], all robot arms and mobile robots were connected to the Open Platform Communications Unified Architecture (OPC UA). The OPC UA Standard [26] is an open-source industrial information server. It's an international IEC 62541 [27] standard and is commonly used today in the manufacturing industry to enable communication between pieces of equipment [28]. It is scale-able and platform-independent, which means it can run on almost all operating systems.

Having all the robots connected to the same server makes it simpler for the machines to communicate. In addition, the robots can be controlled and monitored through the OPC UA server. Since the OPC UA standard is widely supported in the manufacturing industry, it simplifies the integration of new machines into the system.

The IoT system can be structured into five parts, one for each of the robot trolleys, one for the mobile robot, one for controlling the system/generating missions, and the OPC UA server, as illustrated in figure 4.

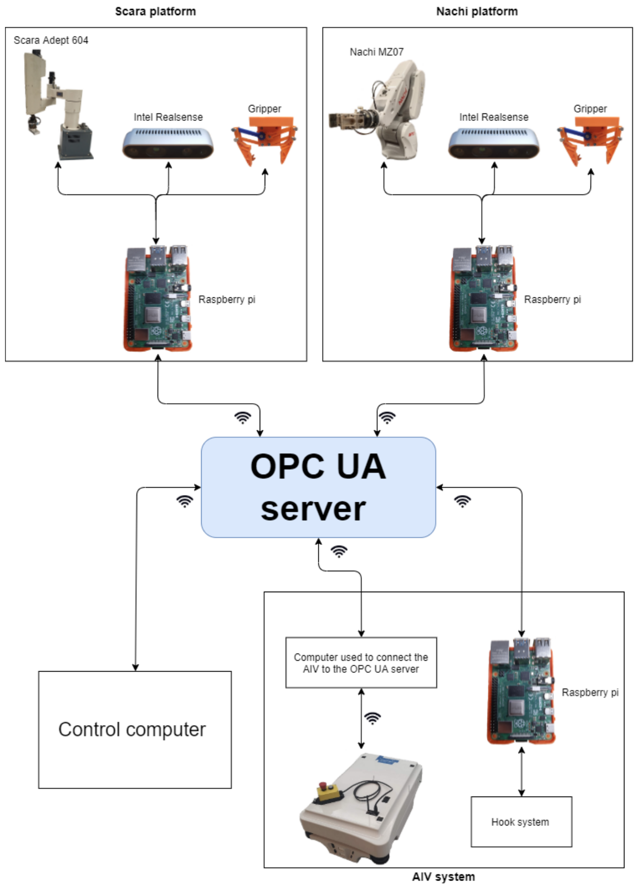

Fig. 4. Illustration on system setup and connections.

As can be seen in figure 4, both robot trolleys is equipped with a single-board computer (Raspberry Pi). It gathers information from the 3D camera and send information to the robot arm and its gripper. There is also a Raspberry Pi on top of the mobile robot, which is used to manage the pins for locking or attaching the mechanism to the trolley. The Raspberry Pis are wireless connected to the OPC UA server.

The mobile robot itself do not support OPC UA, and a computer is used to send and receive information from the OPC UA server.

To start a mission on the Nachi or Adept robot, a computer is used to allocate assignments, which are then started and executed automatically. The Adept and Nachi robots have been made to operate independently from the other parts of the system. Both robot trolleys can control the mobile robot and other machines, for example: call on the mobile robot for transport or get a drawer from the vertical storage lift. The hierarchy of the system can be seen in figure 5.

IV. Demonstration

To showcase the system, we have created three demonstration videos, as can be seen in table I. There are two versions

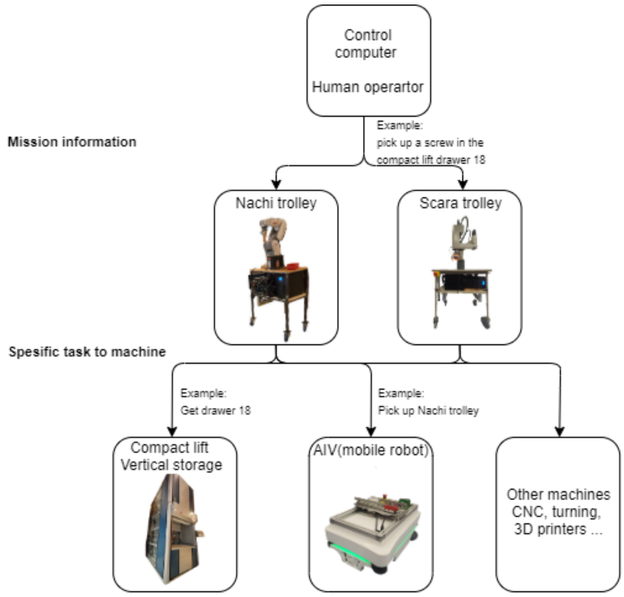

Fig. 5. System control hierarchy.

of each video: one with increased video speed and a second video at normal speed.

TABLE I

THE TABLE LISTS THE FIVE VIDEOS THAT HAVE BEEN CREATED AND INCLUDES A LINK TO THE VIDEOS.

Videos from the demonstration		
Description:	**Speed x5**	**Original speed**
Logistics demonstration	`https://youtu.be/8gyoRbaeshk`	`https://youtu.be/r-DMh_OIFO0`
Nachi pick object	`https://youtu.be/HgNFWy8n560`	`https://youtu.be/q9QY52aMSdE`
Scara pick object	`https://youtu.be/O2DUdpMDWmU`	`https://youtu.be/C13GEO--DRg`

The first video showcases the collaboration between robots in the systems. Four positions/markers have been added to the laboratory. In the demonstration video, the mobile robot transports the Nachi platform, Adept platform and an empty platform around the laboratory to showcase how one mobile robot can be used to transport multiple robots and carry out an logistics operation.

The following happens in the demonstration video:

1) The mobile robot transports the Nachi platform to the Compact lift
2) The Nachi platform calls for a drawer from the Compact lift and starts picking an object(screw)
3) The mobile robot transports the Scara platform to a workstation
4) When the Scara platform has been transported, it starts picking up objects (screw)
5) At the end, the mobile robot transports an empty platform

The other two videos showcase the Nachi and Scara robot picking up a screw using image recognition and the electromagnet.

From the demonstration, we conclude that the mobile robot is able to transport both robot platforms and an empty platform around the laboratory. The mobile robot and the robot arms are also capable of working independently from each other as well as collaborating together.

It should also be noted that using the OPC UA server for communication creates a stable and reliable method for communication between all machines.

The pickup system for the Nachi and Adept robot is relatively simple. A test was conducted on the Scara robot to see how accurate the pick system was. The robot tried to pick up a screw eight times and failed three times which gives room for improvement.

V. Conclusion

The AIMM has proven to be a flexible solution that combines different technologies and concepts. It is intended to be used by manufacturing companies that require more flexibility and personalized production. The AIMM often includes an intelligent mobile robot and robot arm with a vision system that increases the robot's flexibility. However, one of the disadvantages of the AIMM is that it is an expensive investment, and it is therefore essential to get as much utilization of the AIMM as possible.

To increase the utilization and the flexibility of the AIMM, we propose to divide the AIMM into two parts. This creates a more flexible system where we better can utilize both the mobile robot and robot arm, as can be seen in the demonstration.

This system relies on IoT functionality for machine-to-machine communication between the robots. Using the OPC UA standard can be a good and flexible solution for IoT connectivity in industry 4.0 systems. It makes it simple to add more robots or other machines to the system without affecting the other parts and creates unified communication between all members.

The experimental system was tested with a SCARA robot and an industrial Nachi robot. The Scara robot is limited to 4-DOF and therefore has somewhat limited movements. In contrast, the Nachi robot has 6-DOF, has a better reach, and is more suited to work on a mobile trolley. It is also important to keep the robot trolley as light as possible. If the trolley is too heavy, the wheels of the mobile robot will start to spin, which reduces the accuracy of the robot. Therefore, the ideal robot trolley should be equipped with a lightweight robot arm and controller, with a long reach/working area.

A general challenge of having the robot on a portable trolley is that robot movement can transfer to an unstable trolley. A docking system of the portable trolley should be considered as a next step in system development.

VI. Further work

As part of our future work, the vision system should be made more flexible and able to recognize more objects. More intelligence, such as reinforcement learning and neural networks, should also be added to the robot trolleys to make them more flexible and adaptable to the environment. Adding more intelligence to the system can simplify the integration of more capabilities of the robot trolley.

In this system, the mobile robot can only position the robot arms where a marker has been placed. This again limits the flexibility of the system. The positioning could be improved so that the mobile robot can place and pick up the trolley in any given position. Finally a trolley docking system should be developed in order to secure stable IR robot movements.

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References

[1] Ercan Oztemel and Samet Gursev. "Literature review of Industry 4.0 and related technologies". eng. In: *Journal of intelligent manufacturing* 31.1 (2020), pp. 127–182. ISSN: 0956-5515.

[2] "Software-defined Cloud Manufacturing for Industry 4.0". In: *Procedia CIRP* 52 (2016). The Sixth International Conference on Changeable, Agile, Reconfigurable and Virtual Production (CARV2016), pp. 12–17. ISSN: 2212-8271. DOI: https://doi.org/10.1016/j.procir.2016.07.041. URL: http://www.sciencedirect.com/science/article/pii/S2212827116307910.

[3] Alejandro Germán Frank, Lucas Santos Dalenogare, and Néstor Fabián Ayala. "Industry 4.0 technologies: Implementation patterns in manufacturing companies". In: *International Journal of Production Economics* 210 (2019), pp. 15–26. ISSN: 0925-5273. DOI: https://doi.org/10.1016/j.ijpe.2019.01.004. URL: http://www.sciencedirect.com/science/article/pii/S0925527319300040.

[4] Yi Wang et al. "Industry 4.0: a way from mass customization to mass personalization production". eng. In: *Advances in manufacturing* 5.4 (2017), pp. 311–320. ISSN: 2195-3597.

[5] Joanna Daaboul et al. "Design for mass customization: Product variety vs. process variety". In: *CIRP Annals* 60.1 (2011), pp. 169–174. ISSN: 0007-8506. DOI: https://doi.org/10.1016/j.cirp.2011.03.093. URL: http://www.sciencedirect.com/science/article/pii/S0007850611000941.

[6] Brad Hamner et al. "An autonomous mobile manipulator for assembly tasks". In: *Autonomous Robots* 28 (Sept. 2010), pp. 131–149. DOI: 10.1007/s10514-009-9142-y.

[7] Biao Zhang et al. "The challenges of integrating an industrial robot on a mobile platform". In: *2010 IEEE International Conference on Automation and Logistics*. 2010, pp. 255–260. DOI: 10.1109/ICAL.2010.5585289.

[8] Simon Bøgh et al. "Identifying and evaluating suitable tasks for autonomous industrial mobile manipulators (AIMM)". In: *The International Journal of Advanced Manufacturing Technology* 61 (Nov. 2011), pp. 713–726. DOI: 10.1007/s00170-011-3718-3.

[9] Mads Hvilshøj et al. "Autonomous industrial mobile manipulation (AIMM): past, present and future". eng. In: *Industrial robot* 39.2 (2012), pp. 120–135. ISSN: 0143-991X.

[10] H. Cheng, H. Chen, and Y. Liu. "Object handling using Autonomous Industrial Mobile Manipulator". In: *2013 IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems*. 2013, pp. 36–41. DOI: 10.1109/CYBER.2013.6705416.

[11] Rasmus Eckholdt Andersen et al. "Integration of a Skill-based Collaborative Mobile Robot in a Smart Cyber-physical Environment". In: *Procedia Manufacturing* 11 (2017). 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017, 27-30 June 2017, Modena, Italy, pp. 114–123. ISSN: 2351-9789. DOI: https://doi.org/10.1016/j.promfg.2017.07.209. URL: http://www.sciencedirect.com/science/article/pii/S2351978917304171.

[12] Heiko Engemann et al. "OMNIVIL—An Autonomous Mobile Manipulator for Flexible Production". In: *Sensors* 20.24 (2020). ISSN: 1424-8220. DOI: 10.3390/s20247249. URL: https://www.mdpi.com/1424-8220/20/24/7249.

[13] *Welcome to TAPAS*. URL: http://www.tapas-project.eu/. (accessed: 29.12.2020).

[14] *Validation of Advanced, Collaborative Robotics for Industrial Applications*. URL: https://cordis.europa.eu/project/id/314774. (accessed: 29.12.2020).

[15] *KMR iiwa*. URL: https://www.kuka.com/en-de/products/mobility/mobile-robots/kmr-iiwa. (accessed: 29.12.2020).

[16] *Robotics Platforms for Research*. URL: https://fetchrobotics.com/robotics-platforms/. (accessed: 29.12.2020).

[17] *Omron Mobile Manipulator Solution*. URL: https://industrial.omron.eu/en/solutions/product-solutions/omron-mobile-manipulator-solution. (accessed: 29.12.2020).

[18] *ER-FLEX*. URL: https://www.enabled-robotics.com/er-flex-robot/. (accessed: 29.12.2020).

[19] *Mobile Manipulators*. URL: https://robotnik.eu/products/mobile-manipulators/. (accessed: 29.12.2020).

[20] Ole Madsen et al. "Integration of mobile manipulators in an industrial production". In: *Industrial Robot: An International Journal* 42 (Jan. 2015), pp. 11–18. DOI: 10.1108/IR-09-2014-0390.

[21] Mobile Industrial Robots. *MiR100*. URL: https://www.mobile-industrial-robots.com/en/solutions/robots/mir100/. (accessed: 023.11.2020).

[22] OpenCV team. *OpenCV*. URL: https://opencv.org/. (accessed: 24.11.2020).

[23] OpenCV team. *About*. URL: https://opencv.org/about/. (accessed: 25.11.2020).

[24] Mads Hvilshøj and Simon Bøgh. ""Little Helper" — An Autonomous Industrial Mobile Manipulator Concept". In: *International Journal of Advanced Robotic Systems* 8.2 (2011), p. 15. DOI: 10.5772/10579. eprint: https://doi.org/10.5772/10579. URL: https://doi.org/10.5772/10579.

[25] H. Arnarson, B. Solvang, and B. Shu. "The application of open access middleware for cooperation among heterogeneous manufacturing systems". In: *2020 3rd International Symposium on Small-scale Intelligent Manufacturing Systems (SIMS)*. 2020, pp. 1–6. DOI: 10.1109/SIMS49386.2020.9121537.

[26] M. H. Schwarz and J. Börcsök. "A survey on OPC and OPC-UA: About the standard, developments and investigations". In: *2013 XXIV International Conference on Information, Communication and Automation Technologies (ICAT)*. 2013, pp. 1–6. DOI: 10.1109/ICAT.2013.6684065.

[27] OPC Foundation. *Unified Architecture*. URL: https://opcfoundation.org/about/opc-technologies/opc-ua/. (accessed: 01.02.2021).

[28] OPC Foundation. *Unified Architecture*. URL: https://opcfoundation.org/about/opc-technologies/opc-ua/. (accessed: 25.11.2020).

Paper 2

Towards automatic configuration and programming of a manufacturing cell

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Author's Contribution

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

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Towards automatic configuration and programming of a manufacturing cell

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ABSTRACT

Manufacturing industries are moving from mass production towards customized production, aiming for high-quality products with innovative technologies, low prices, and high reliability. A reconfigurable manufacturing system (RMS) is an attractive approach to facilitate the movement toward such flexible manufacturing systems. However, reconfiguration and programming of RMS are time-consuming and labor-intensive. Industry 4.0 technologies (such as robotics, digital twin technology, and IoT solutions) decrease human interaction in the preparation phase of a new production series. One challenge that industry 4.0 does not address is a flexible electrification of the system. The lack of electrical outlets limits the available space on the shop floor, and extensive cabling constrains the motion of humans and machines in the same area. This paper solves these challenges by proposing a highly flexible RMS system with advanced robotics, a digital twin programming interface, and a wireless power transfer (WPT) solution. Experimental results, through simulations and verification by laboratory experiments, show great potential in the reduction of human interaction and time to set up a new manufacturing line.

1. Introduction

Globalization has put intense competition between manufacturing companies to produce high-quality products with innovative technologies, low prices, and high reliability. The increasing competition between manufacturers motivates them to move away from mass production towards mass customization and personalized production [1]. Competitors need to adapt and change depending on the market changes, product changes, system failures [2], or global health crises [3].

We can categorize manufacturing systems into three main categories; dedicated manufacturing system (DMS), flexible manufacturing system (FMS), and reconfigurable manufacturing system (RMS). The DMS focuses on high volume and low variety production, while the FMS focuses on low volume and wide variety. In contrast, RMS combines the advantages of both systems to produce with high volume and wide variety. Koren et al. [4] defined RMS as a manufacturing system that can adjust its resources. Thus, RMS is an attractive approach to solve the previously mentioned challenges.

Reconfiguration of RMS can be time consuming. Kim et al. [5] found that in their RMS, the most time-consuming part is the physical rearrangement of the modules and reconfiguring of the system. The system also needs physical labor to rearrange or change the modules in the manufacturing system. As the RMS is scalable, increasing the size of the system results in scaling up the RMS challenges. In other words, with the increasing number of modules of the RMS, the reconfigurable time increases, and the required labor to reconfigure the system will also increase. Moreover, increasing the system scalability adds more demand on the computation, communication, and system complexity [6].

Industry 4.0 is the next technological revolution that focuses on increasing connectivity, automation, and intelligence in manufacturing [7]. The technologies in industry 4.0 are advanced robotics, the internet of things (IoT), cyber-physical systems (CPS), cloud computing, augmented reality, additive manufacturing, and big data are essential for the success of RMS in the future [8]. Industry 4.0 technologies can improve and automate the rearrangement of RMS. However, Bortolini et al. [9], revealed that there is still a lack of research on industry 4.0 integration in RMS. Maganha et al. [10] mentioned that using industry 4.0 technologies must be considered when designing the layout of the system and that the technologies can allow for smart layout design of the RMS.

Morgan et al. [11] suggested that there is a need to retrofit current

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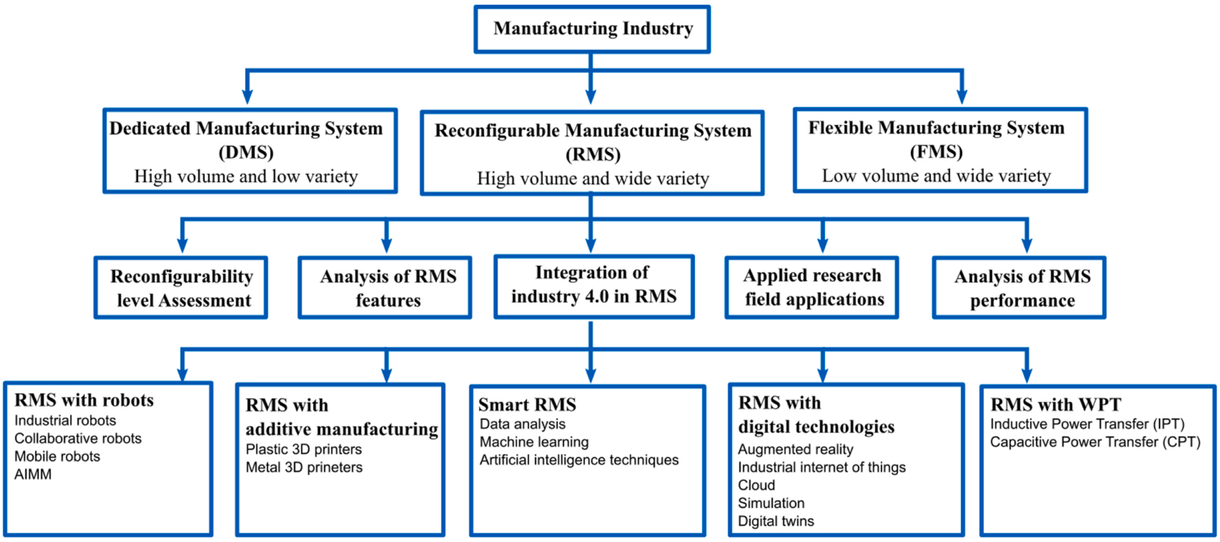

Fig. 1. The research direction for RMS based on Bortolini schematic [9], with a focus on industry 4.0 integration to RMS.

manufacturing equipment with the new technologies. Thus, we can retrofit old robots with new controllers, IoT functionality, and adaptable control systems. Using advanced robotics, IoT, and digital twins, we can control and automate the reconfiguration of RMS. The robots can rearrange the modules in such a system, while the IoT offers wireless control and communication.

Although industry 4.0 tackles most RMS problems, there is still a challenge with electrification. Systems need labor to connect all parts to power, and it is time-consuming. Besides, the conventional electrification uses cables that require large areas, which limits the flexibility of the systems. Therefore, there is a need for more flexible methods to power RMS without human intervention. Wireless power transfer (WPT) can energize the system autonomously and has the potential to address the challenges in the conventional conductive charging approach, including long charging time, wear and tear of the contractors and plugs, and hazard of the electric shock.

To the authors' knowledge, there is no publications which use mobile robot to rearrange the machines in the manufacturing cells. Arnarson et al. [12] used one mobile robot to move multiple robot arms. We can expand this conceptual idea by moving different manufacturing machines using a mobile robot. In addition, there is no investigation of WPT for manufacturing systems or consideration of WPT as an industry 4.0 technology. Industry 4.0 is a dynamic concept where various technologies are in industry 4.0 can and will change over time [7]. For instance, one of the main technologies in industry 4.0 is IoT which can connect devices wirelessly. WPT provides wireless electrification of systems, we can argue that WPT is a new and emerging industry 4.0 technology that can allow manufacturing systems to become more flexible, modular, and automated.

Expanding Bortolini framework [9], we can categorize the research directions of industry 4.0 in RMS, as shown in Fig. 1. The first industry 4.0 technology is RMS with robots, including industrial robots, collaborative robots, mobile robots, and autonomous industrial mobile manipulators (AIMM) in RMS. RMS with additive manufacturing looks at implementing 3D printers into the system. RMS with digital technologies which embrace augmented reality, industrial internet of things (IIoT), cloud, simulation, and digital twins. Smart RMS encompass data analysis, machine learning, and other artificial intelligence techniques. Finally, RMS with WPT looks at flexible and autonomous electrification for manufacturing systems.

In this paper, we propose an autonomous RMS by integrating a mobile robot into RMS, to increase the reconfigurability of the system, decrease the setup and programming time, and enhance the system's flexibility. Besides, we investigate different WPT configurations that increase flexibility and autonomy, creating a highly flexible RMS. We can summarize the main contribution of the paper as follows: .

- Proposing a new RMS in which a mobile robot can reconfigure the system.
- Rearranging, and monitoring the proposed system using a digital twin solution.
- Proposing static and dynamic WPT as industry 4.0 technology for RMS.
- Retrofitting old manufacturing machines with industry 4.0 technology.
- Simulating and verifying through laboratory experiments and video presentations.

We organize the remainder of this paper as follows: Section 2 presents previous studies on RMS. Section 3 proposes the concept of a highly flexible mobile RMS with WPT. Section 4 describes a mobile RMS with a digital twin, a physical demonstration of the system. Then, we discuss the results in Section 5. Finally, we conclude and present our future works in Section 6.

2. Previous studies

Sanderson et al. [13] developed the Smart Manufacturing and Reconfigurable Technologies (SMART), which is an assembly system that can be set up with different configurations. The system is based on the HAS-200 system [14] and applies adaptive multi-agent control. There are other similar examples on smart RMS [15–18]. They used standardized platforms from the CP Factory. CP Factory is a universal modular manufacturing systems for research, training, and teaching, produced by FESTO [19]. The systems use platforms that can be rearranged based on the system's capacity and functionality.

In another study, Kim et al. [5] introduced a modular factory testbed. The system consists of 10 main workstations producing portable battery chargers, electric endodontic handpieces, and electric toothbrushes. The system uses a infrared communication system that automatically recognizes how the system is configured. However, all the previous systems (i.e., CP factory, HAS-200, and testbed) are only used for training, educational, and research purposes.

Adamietz et al. [20] presented a miniaturized RMS. The system uses a standardized container, in which it is possible to change the manufacturing modules inside the container. This system can have a

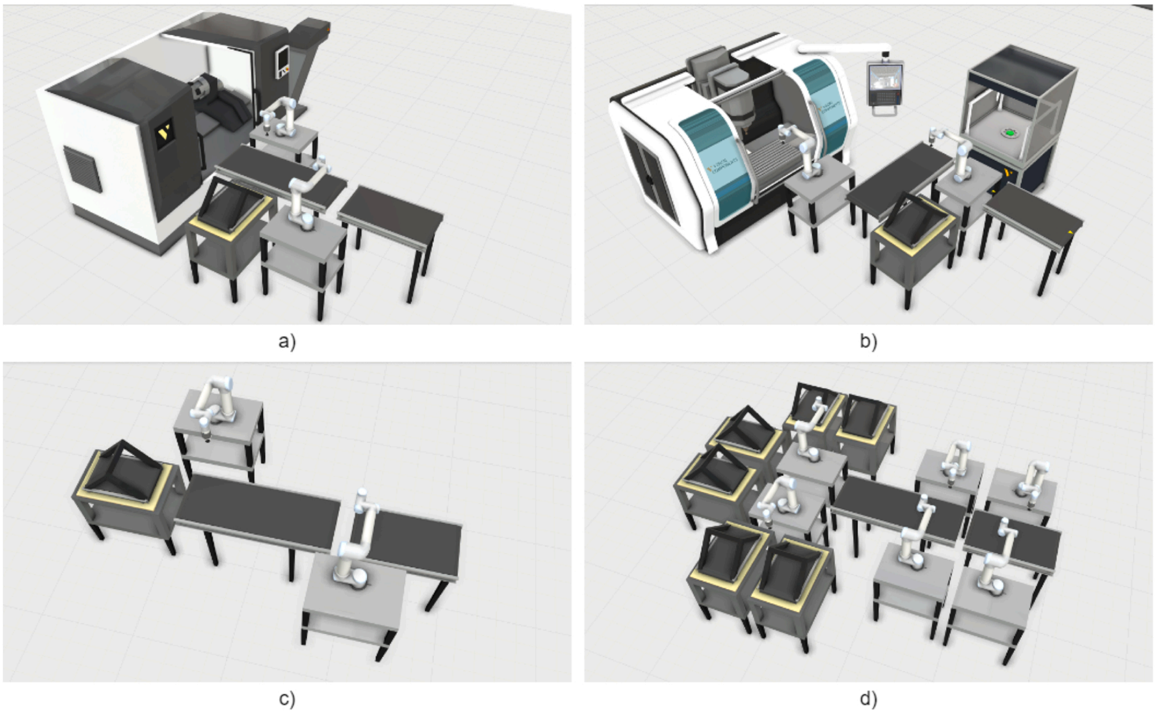

Fig. 2. Different examples of how the system can be configured (a, b) and scaled up and down (c, d): (a) The platforms are arranged around the turning center, (b) the platforms are arranged around a large 3D printer, (c) a small manufacturing system using the platforms, and (d) the previous manufacturing system is expanded with more platforms to increase production.

maximum of six small modules, three large modules, or a combination of big and smaller modules. The system reconfiguration takes less than 8 h using a forklift, where a human needs to move the parts between the machines.

Seok et al. [21] built a modular manufacturing system using the additive manufacturing concept. Their system consists of, 3D printers, post-processing, inspection, and packing modules. It uses a 3D printer as the main manufacturing process, and it is possible to achieve personalized production or mass customization. We can categorize the system as an RMS with digital technologies.

One approach that can save time and automate the RMS is the AIMM principle. Hongtai et al. [22] explained the concept of AIMM as a mobile robot combined with an industrial manipulator. The robots are easy to integrate and can carry out tasks at different workstations. The AIMM increases manufacturing flexibility and we can implement it into existing manufacturing systems [23]. Recently, Inoue et al. [24] proposed AIMM to be a key component of RMS. Andersen et al. [25] examined how to integrate an AIMM into a modular CP Factory.

Regardless of these previous studies, there is little attention to building and designing RMS for manufacturing industries. For instance, Singh et al. [26] revealed that there is inadequate research on the development of principles for reconfigurable machines. Moreover, Khanna et al. [27] found that the implementation of RMS into manufacturing systems is still a significant problem. In addition, there is a lack of studies that explain RMS in practices and how RMS can be adapted and used by companies [28].

The previous studies showed that the physical reconfiguration of the platforms is the most time-consuming, and they require labor to change and modify the layout. Morgan et al. [11] proposed smart reconfigurable machines that can change autonomously. In another study, Singh et al. [26] found that there is immense potential for further research on wireless sensor networks for automatic configuration, interoperability, and scalability.

WPT plays a crucial role in charging applications without human intervention, making it attractive for developing flexible and reliable RMS systems. It reduces the hazards of electrical shocks by plugin cables. It can also minimize the systems' maintenance by removing the plugs, cables, and contractors. WPT provides an attractive solution in different applications: IoT devices [29,30], lightning [31–33], heating [34], wind turbines and oil drilling tools [35], energy encryption [36], unmanned aerial and underwater vehicles [37–40,41], and transportation applications [42–44].

To summarize, we found there is less focus on industry 4.0 integration. Moreover, all the previously proposed systems suffer from setup, layout, and programming restrictions. In addition, systems are still highly dependent on humans for reconfiguration and powering the system. If we use advanced robotics, IoT, and digital twin to rearrange the system, this can improve the flexibility and reconfigurability of the system. At the same time, implementing WPT will make manufacturing systems more flexible, modular and automated and support the other industry 4.0 technologies.

3. Concept of a highly flexible system

3.1. RMS with robots

To integrate industry 4.0 in RMS, we can use the concept of AIMM to utilize robots in a flexible manner. Arnarson et al. [12] proposed an AIMM for RMS, where the AIMM is divided into two separate parts, one for the mobile robot and a second for a robot arm. The mobile robot and robot arm can work together or separately. With such a system, one mobile robot can move multiple platforms and increase the utilization of both the robot arm and the mobile robot. In this example, they created two robot platforms. Using the same principle, we can expand the idea by adding conveyors, 3D printers, or other manufacturing machines to the platforms instead of a robot arm.

A mobile robot can move and rearrange all system parts to manufacture a specific product. The mobile robot can also rearrange around large manufacturing machines (CNC, turning, and 3D printer) that are fixed and hard to move. This solution is scalable since adding new

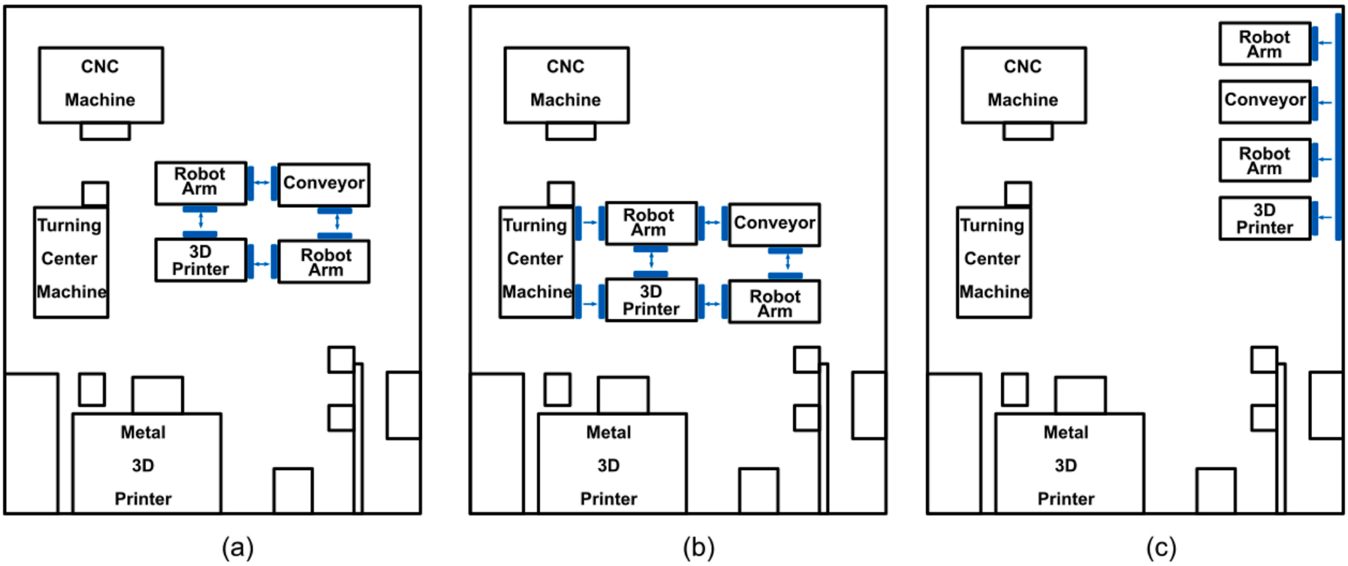

Fig. 3. A top-view of three different scenarios for static WPT: (a) the platforms charge each other through a mesh configuration. (b) the platforms charge each other through a mesh configuration while a big machine energizes the whole system. (c) the platforms charge from the main source while they are parking.

platforms to the system can increase the output and production capacity. Therefore, it is easy to downscale and upscale production based on demand. Fig. 2 shows how to configure the system with different scalable layouts. At the same time, we can also use collaborative robots in open environments where humans are working or industrial robots for tasks that require higher precision and accuracy.

3.2. 3D printing

Another emerging industry 4.0 technology is additive manufacturing, in which we can get an even more flexible and automated RMS. For instance, in the conventional manufacturing approach to produce a plastic box, we need to build a mold and other related manufacturing machines that are not flexible. In comparison, plastic 3D printer can produce a plastic box or any other plastic part. In other words, additive manufacturing can increase the mass customization capability of the RMS. In this video https://youtu.be/Z6WQe1bf648 and in [45], we demonstrate how a flexible additive manufacturing in RMS in which a plastic 3D printer can print different parts automatically and a mobile robot pick up the 3D printer and move it to different places. In addition, we can use the manufacturing material more efficiently and produce less waste.

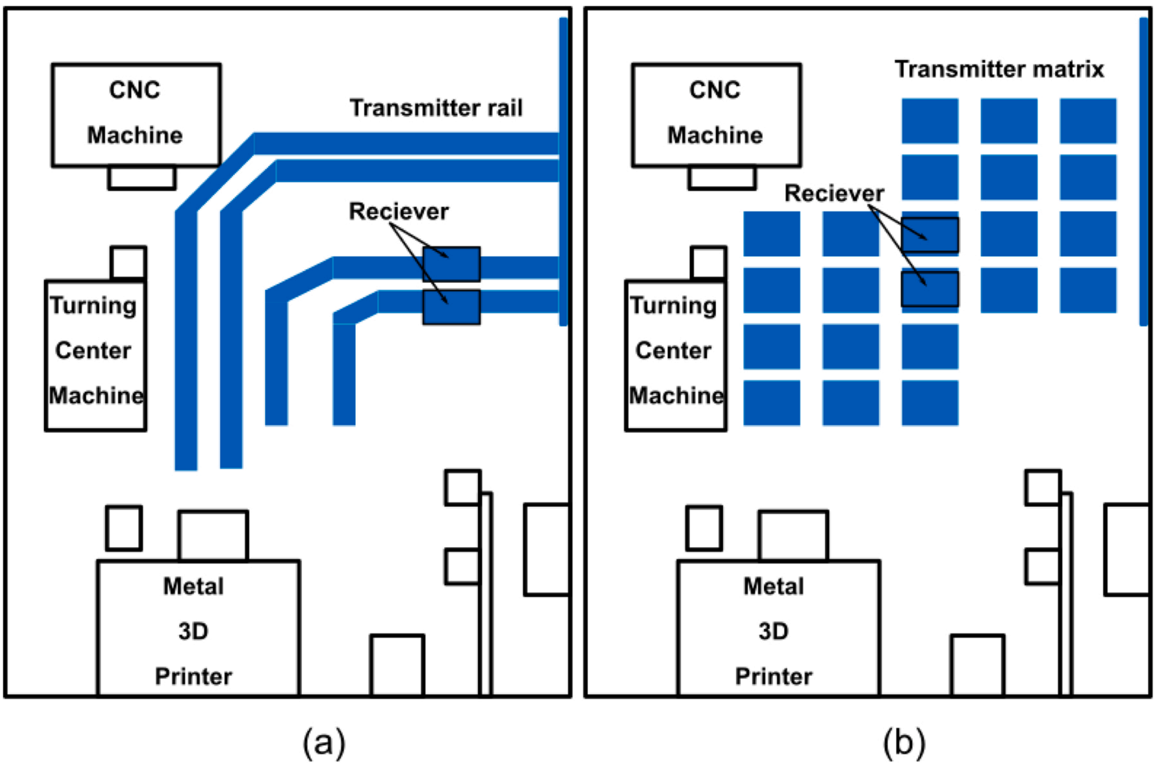

Fig. 4. A top-view of two approaches of dynamic WPT: (a) railway transmitters. (b) matrix transmitters.

3.3. Digital technologies

IIoT facilitates communication, allowing remote monitoring and control of the manufacturing system. Thus, we can retrofit the conventional manufacturing systems with IIoT to create communication between machines in the system. Besides, we can simulate the system to see how the reconfiguration and layout of the system will look in reality. The disadvantage of having only offline simulation is that we cannot test the RMS in real-time. It cannot be used for control or monitoring the RMS. In addition, the current solution for manufacturing systems is basic human-machine interfaces, where the labor communicates with the machines through a screen. This type of interface makes it difficult to program a reconfiguration of the manufacturing system.

However, if we use the digital twin of the system to test and see how the configuration looks and works. The digital twin is a real-time digital replica of the manufacturing system where we can transfer the data bidirectional between the physical and digital systems. Based on a digital twin we can simulate [46], control [47], monitor [48], predict failures of the system. In this paper, we simulate and monitor the system at the same time using a digital twin principle.

3.4. Smart RMS

Arnarson et al. [49] introduced industrial big data in RMS, for a smarter RMS system. In this work, they used the principles of industrial big data analysis moving towards automated RMS. Industrial big data analysis combined with artificial intelligence moves us toward a fully automated manufacturing system in which the system can manufacture any products without human intervention.

3.5. RMS with WPT

It is hard to achieve fully automated manufacturing systems with a conventional wired electrification approach. If we use WPT, we can gain autonomous electrification of the system and hence a fully automated system. Besides, WPT provides more flexibility and reliability to the RMS. In this section, we introduce the main concept of WPT to industry 4.0 technologies and give examples of static and dynamic implementation of WPT in RMS, while we provide more detailed descriptions and experimental results in further work.

The International Telecommunication Union defines WPT as the transmission of power from a power source to an electrical load wirelessly using a electromagnetic field [50]. WPT incorporates three main groups: near-field, mid-range, and far-field. The differences between these groups are in terms of the type of the electromagnetic wave, distance range, operating frequency level, power level, and the complexity of the system's architecture.

We can utilize either static or dynamic near-field WPT for RMS. The static approach offers electrification when the platforms are not moving. Fig. 3 illustrates three different scenarios. The arrows show the direction of the power flow. In scenario (a), we can fix the WPT transmitter-receiver on the platforms while electrifying each other through a mesh configuration. In contrast, in scenario (b), the platforms energize from a stationary machine, such as a turning center, while charging. The last scenario (c) is when the platform is not in use and charges from the main power source.

On the other hand, dynamic WPT can offer a power source for the platforms and mobile robots. We can implement the dynamic WPT through two approaches, namely, the railway approach and matrix one, as shown in Fig. 4. The railway transmitters provide continuous power to the platforms in the railway approach. However, the allocation of the platform should be predetermined, which limits the flexibility of the RMS. In contrast, the matrix approach offers a flexible charging solution. Nevertheless, it provides discrete charging, and hence we should optimize the distance between the transmitters, increasing the complexity and cost of the WPT system.

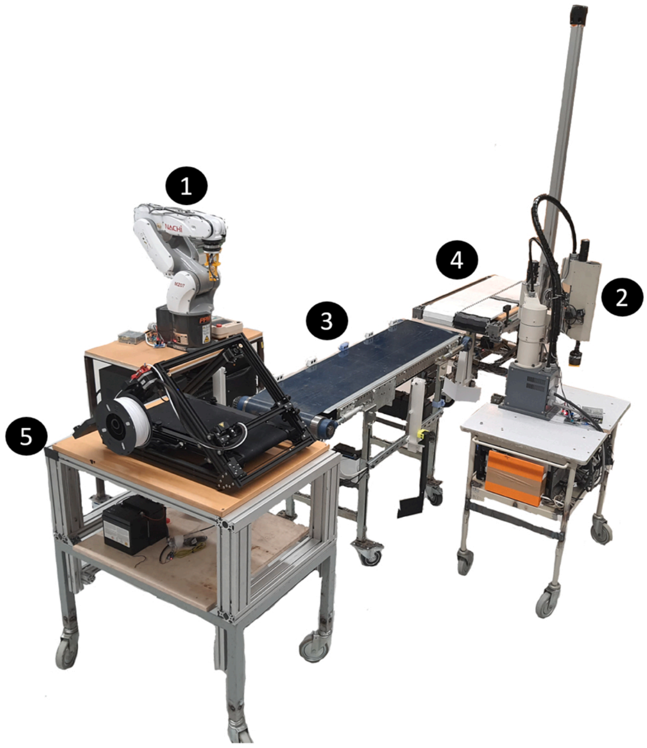

Fig. 5. The proposed RMS: (1) IRB1 platform, (2) IRB2 platform, (3) conveyor, (4) conveyor with lifting, and (5) 3D printer.

4. Reconfigurable manufacturing system

In this section, we describe the RMS and give a demonstration both by simulation and testing.

4.1. RMS description

Our system consists of five platforms:

- **IRB1 platform:** Has a four degree of freedom robot arm (SCARA-type). In this system it is used for simple assembly, pick and place and sorting operations.

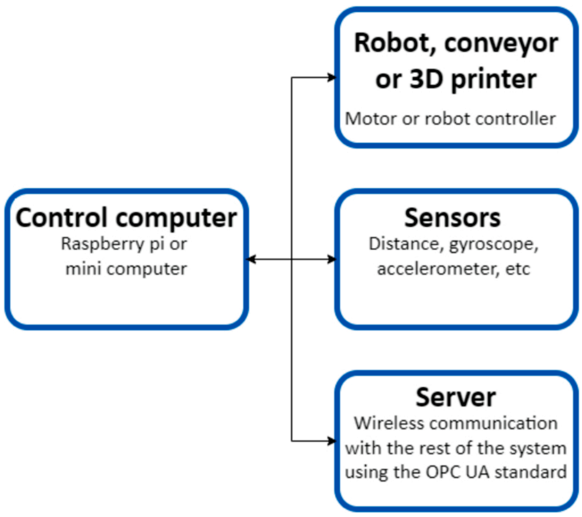

Fig. 6. The main components on each platform.

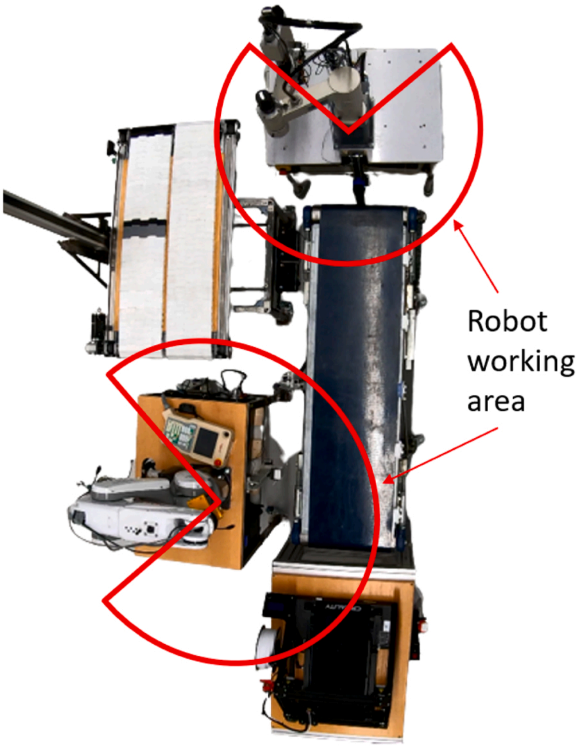

Fig. 7. An illustration of the placement requirements of the system.

- **IRB2 platform:** Is a six degree of freedom robot arm. The robot arm can be used for the same operations as the IRB1 robot, but can also do more complex tasks such as machine tending, polishing, etc.
- **Conveyor platform:** The conveyor platform is used to transport the parts between the robot arms.
- **Conveyor with lifting platform:** Is used to transport parts out of the manufacturing system. Since it has a lift module it is more adaptable then the conveyor platform.
- **3D printer platform:** The 3D print platform contains a Creality CR-30, which is a 3D printer that prints on a conveyor. It can automatically remove the parts as they are being printed.

Fig. 5 shows a specific setup of the RMS.

We have developed the platforms by retrofitting them with small single-board computers and sensors. We have used different sensors to measure distance, angular velocity, and acceleration. As the robot arms require a more powerful computer, we have used (i5–10210 U CPU) to run the inverse kinematics calculator in ROS MoveIT and image recognition models in parallel. While the conveyor, conveyor lift and 3D printer platform use a Raspberry pi for control. All the computers are equipped with WIFI for wireless communication and we have also utilized extra microcontrollers on some of the platforms to collect data and control motors. Fig. 6 depicts the setup of each platform.

A MiR100 mobile robot transports the platforms to the selected location. It has a carrying capacity of 100 kg and can pull up to 300 kg [51]. The accuracy of the mobile robot is $\pm$ 50 mm, which limits the flexibility of the system [12]. The low accuracy of the mobile robot can deteriorate the docking reliability of the platform. Nevertheless, a marker solution is used and enhance the docking accuracy of the mobile robot within $\pm$ 5 mm [51].

We can describe the docking sequence as follows: First, once the mobile robot reaches in front of the platform it adjust itself to the marker. Second, the marker moves up, so the mobile robot can drive under the platform. Third, the mobile robot drives forward with a fixed distance. Fourth, the hooking system is activated and fasten the mobile robot with the platform. A demonstration video to show the docking and uncoupling sequence can be fund at https://www.youtube.com/watch?v=RtOX0HGiqRs. When the mobile robot uncouples from a platform, the mobile robot software saves the platform's position. Besides, the mobile robot calculates and saves 1.5 m from the platform as the docking point for the mobile robot.

For communications the platforms are connected to the Open Platform Communications Unified Architecture (OPC UA). The OPC UA is a IEC 62541 standard and is used for communication in industrial applications [52]. It allows all platforms to connect to the same server and communicate seamlessly which facilitates the control of the robots, conveyors and other motors in the system. This communication protocol will also help to bring about machine-to-machine communication, and hence all platforms can operate without human intervention.

4.2. Platform placement

As mentioned in Section 2, reconfiguring of the RMS can be time consuming and often needs human labor. The idea behind this system is

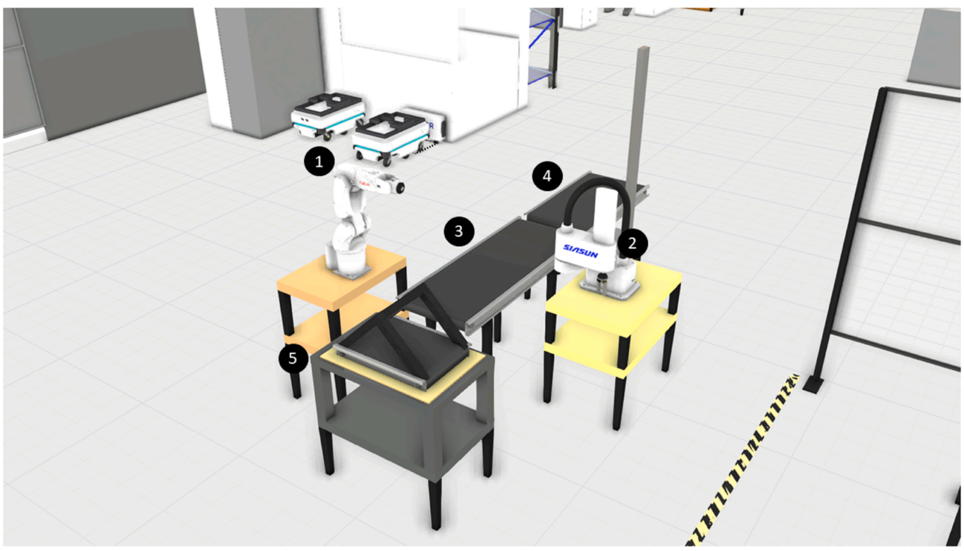

Fig. 8. A screenshot from Visual Components showing the digital twin of the platforms. (1) IRB1 platform, (2) IRB2 platform, (3) conveyor, (4) conveyor with lifting, and (5) 3D printer.

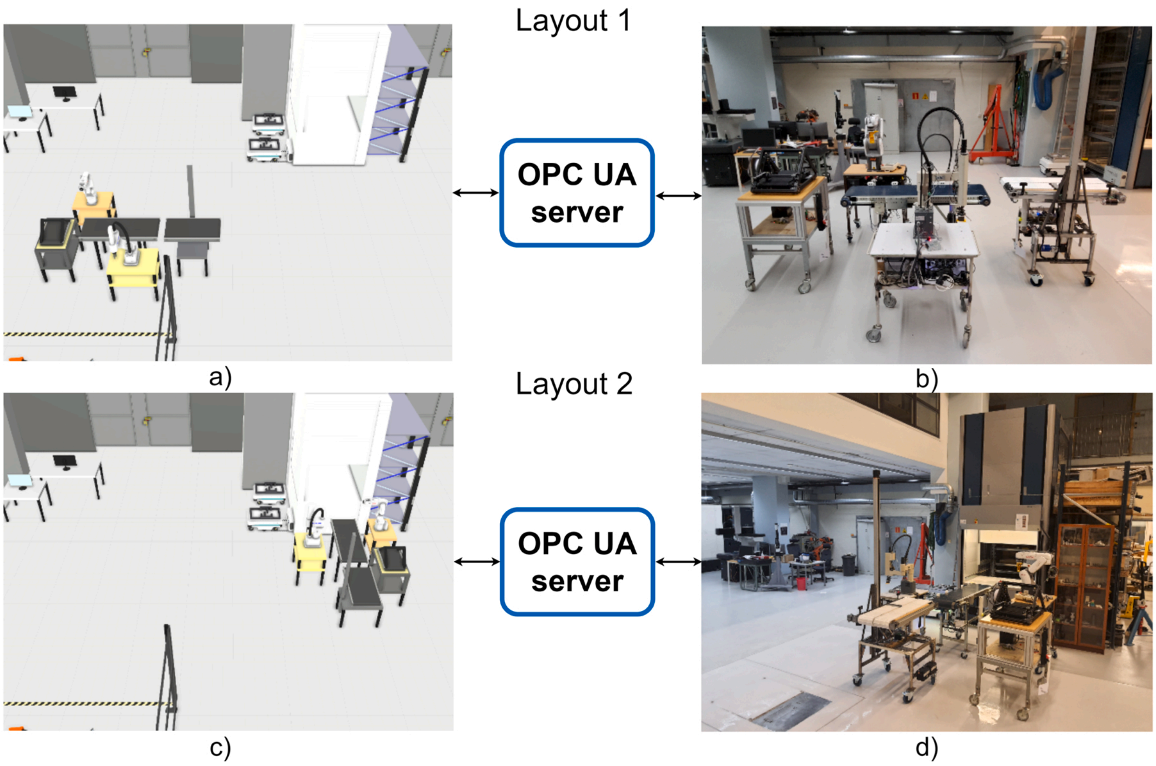

Fig. 9. Two layout configurations in the Visual Components (On the left side), and the resulting configuration assembled with the mobile robot (on the right side): a) The first digital layout. b) The first physical layout. c) The second digital layout. d) The second physical layout.

to reconfigure and change the system's layout automatically with a mobile robot. Also, we can change the layout of the system based on demands. However, the system still faces some challenges. For instance, the IRB1 robot has a movement radius of 0.6 m, while the IRB2 robot has a maximum reach of 0.9 m. For this system to work, the robot arms need to reach the platforms they are working with, as shown in Fig. 7, which add a constraint on system's arrangement. One way to tackle the challenges of choosing the layout of our system is by using a digital twin solution.

Van Der Horn et al. [53] have described the digital twin as a virtual representation of a physical system, where the virtual and physical systems share the data. The virtual model of the manufacturing system can be used to test and visually various configurations of the layout. We can also use it to send information about the placement of the platforms. In addition, we can combine a digital twin with a modular system to create fast reconfiguration, integration, and safety validation of the system [3].

Previously, Arnarson et al. [54] have developed a two-way digital twin model in the Visual Components Premium simulation software [55] and conducted laboratory testing of the system. As Visual Components Premium supports the OPC UA standard, we can use the digital twin model as a visual tool to plan the system's layout and simulate assembly and production flow for different system layouts. Fig. 8 shows the digital twin model of the five platforms. The model in the software has the same scales and positions of the components as the physical system. The simulation takes the positions of the digital platforms and sends them to the OPC UA server. The mobile robot can automatically get the new coordinates of the platforms and start moving them. Eventually, the simulation software decides how the mobile robot picks the platform.

4.3. Demonstrations of the RMS system

Two demonstrations show the functionality of our system.

Table 1
The time the mobile robot used to reconfigure both layouts measured in minutes.

	Layout 1	Layout 2
IRB1 Platform	2.2	2.2
IRB2 platform	2.2	2.3
Conveyor platform	2.1	2.9
Conveyor Lift	2.0	1.9
3D print platform	2.3	2.6
Total time [min]	10.8	11.8

4.3.1. Demonstration of simulation design

The first demonstration shows the automatic reconfiguration. Two layouts are created in the Visual Components model, and when the simulation is executed the positions of the platforms are sent to the server. Afterwards, the mobile robot reads the positions of the platforms from the OPC UA server and pick up and place the platform in the same position given by the model in Visual Components. The resulting configuration of the mobile robot can be seen in Fig. 9.

A video demonstration shows the functionality of the system and can be found at https://youtu.be/UXUlaawd8Ps with 5x speed and another video https://youtu.be/s8r-Q5eMy2M with normal speed. The purpose of the video is to showcase how the mobile robot can automatically change a manufacturing system's layout. The video starts with all platforms in different locations in the laboratory. Then mobile robot picks the platforms and places them into the configuration in Fig. 9. Second, the mobile robot takes apart the system and reconfigures a new manufacturing system with the vertical storage machine (Compact lift). The time it takes to move and place each platform and the total time of the configuration can be found in Table 1.

4.3.2. Demonstration of production simulation

In the second demonstration, we showcase the flexibility and reconfigurability of the system in the simulation model. For this experiment, we use the process modeling component of Visual

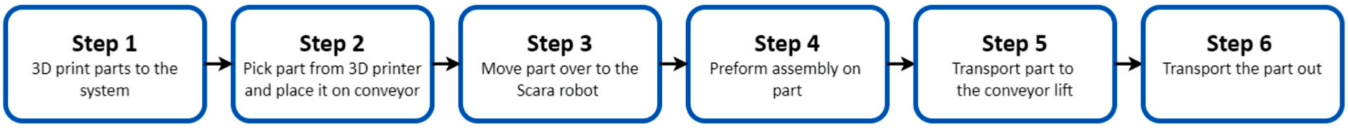

Fig. 10. The production sequence used to produce and assemble a box in the simulation.

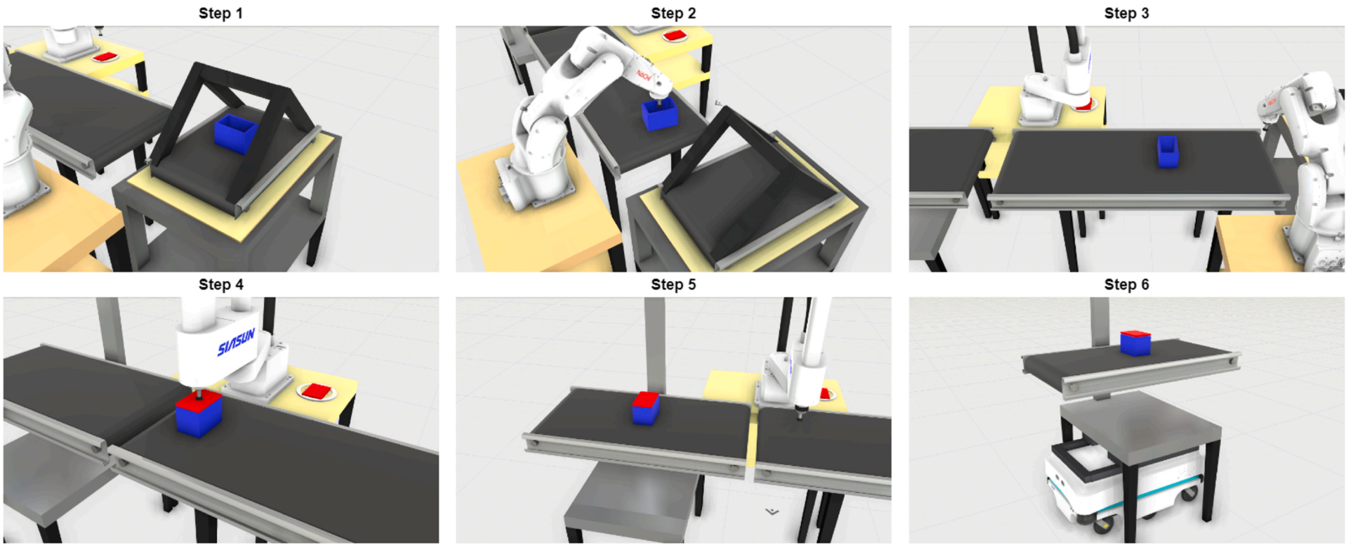

Fig. 11. An illustration of each step in the simulation.

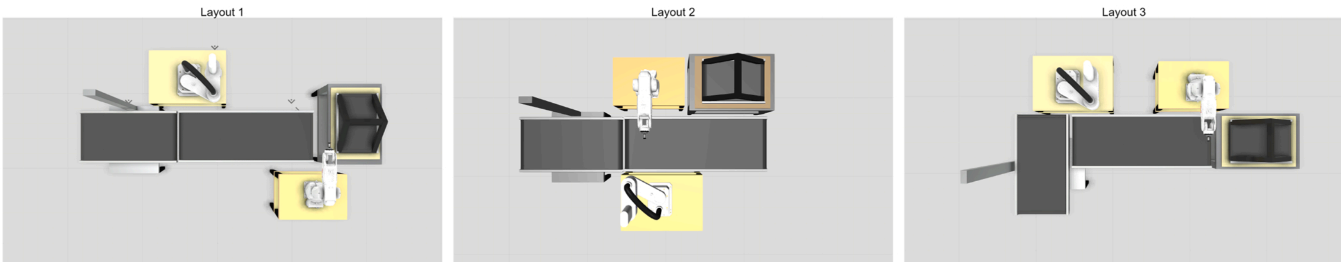

Fig. 12. Three different layout configuration to produce the box.

Table 2
The time it takes to complete each step in the simulation, without considering the 3D printing time measured in seconds.

Manufacturing setup	1	2	3
Step 1	4.6	4.6	4.6
Step 2	3.0	2.8	2.6
Step 3	11.3	2.4	9.8
Step 4	3.1	3.6	3.3
Step 5	10.1	9.5	2.9
Step 6	17.6	17.5	25.0
Total time [sec]	49.7	40.4	48.2

Components to program the system's movements. The simulation shows the production and assembling of a box in six steps, as shown in Fig. 10. The production process are: a box without a lid is 3D printed with the 3D printer platform. When the box reaches the end of the 3D printer, the IRB2 robot picks up the box and places it on the large conveyor. The conveyor transports the box to the IRB1 robot, which takes the lid and places it on top of the box. At last, the box is transported over to the conveyor lift, and the mobile robot transports the conveyor lift out. Fig. 11, illustrates all steps.

We can execute the same production plan of the box with different configurations and placement of the platforms. To test this, we create three different configurations, as can be seen in Fig. 12. A video demonstration https://youtu.be/6ir7RUN_uk0 of the three simulations shows a different production time for each layout. Table 2 lists the production times for each step in all three layouts. We can use the simulation to estimate the production time and test if there are any collisions in the simulation.

4.4. Demonstration of manufacturing application

To demonstrate a manufacturing application of the system, we simulate and implement an assembly of a manufacturing system around a CNC machine. In the simulation, the first step is to drag the platforms and rearrange them around the CNC machine. The second step is to check if the robot arms can reach the positions. The last step, using the digital twin we can transfer the positions of all the platforms to the mobile robot where it reconfigures the platforms automatically. Fig. 13 shows the demonstration of the proposed RMS for manufacturing application. The video https://youtu.be/vxsg4zgJzTU demonstrates the aforementioned three steps. The results shows the system needs around 12.75 min for rearranging around the CNC machine. In this demonstration, we can use one mobile robot to fill raw material to the CNC

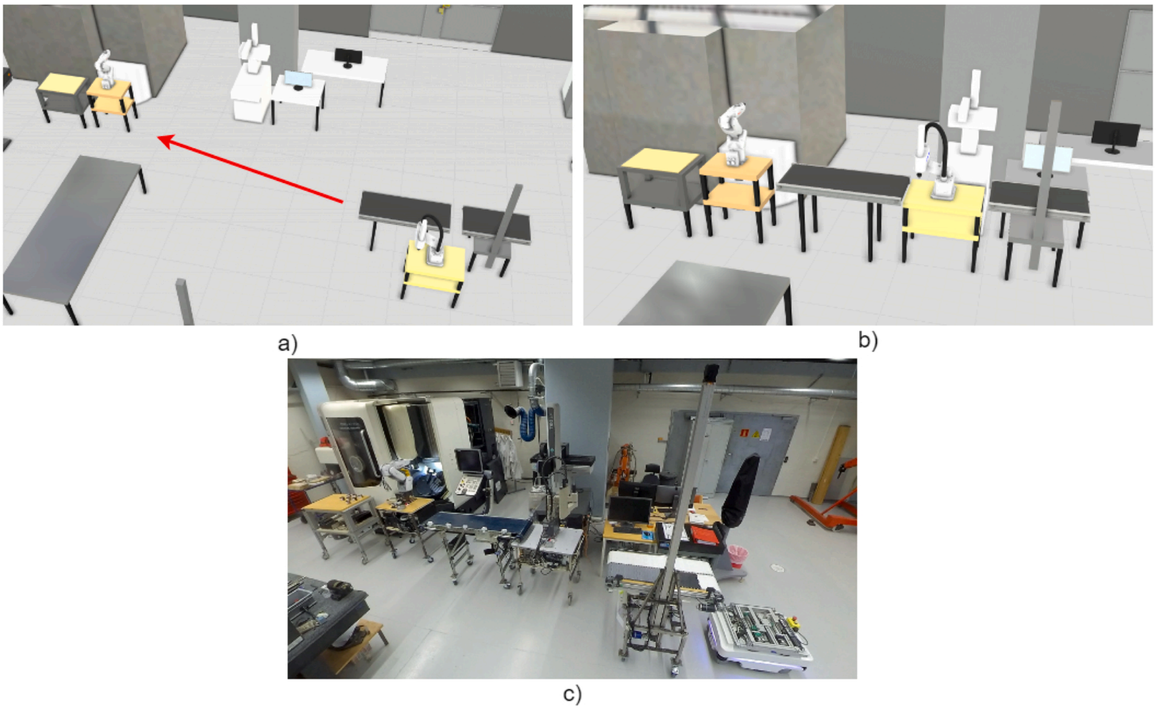

Fig. 13. Demostration of industrial application: a) Configuring the platforms around the CNC machine. b) Simulating to check that the robot arm can reach their position. c) The physical configuration of the platforms around the CNC machine.

machine, rearrange the system, and take out the manufactured products.

5. Discussion

Traditionally, RMS need human interaction to reconfigure the system. In this paper, we have proposed a new RMS solution that decreases the need for humans in the setup of a new manufacturing line. A mobile robot can reconfigure the platforms without any human intervention. A total reconfiguration of the system requires 10:8 min to (numerical range) 11:8 min depending on the layout.

We utilized additive manufacturing as an industry 4.0 technology to produce various products. We simulated three different layouts to manufacture a box using a 3D printer. According to the simulation, the production time took 49.7 s, 40.4 s, and, 48.2 s, respectively, without considering the 3D printing time. However, this was a simple example of producing one type of product, but the 3D printer can print any part as long as it fits within the dimensions of the 3D printer. Besides, using a 3D printer for production can easily automate the production process. Thus we create a platform with a 3D printer that can be controlled, operated, and monitored remotely.

Using industry 4.0 digital technologies, we retrofitted old machines with sensors and controllers, and by applying the IIoT, we got communication between all parts of the system. We used a two-way digital twin with simulation to program the system and choose the layout of the platforms. It gives the operator a simple drag and drop interface to position the platforms. We can also simulate the manufacturing process to test and see if the robot arm reaches its desired position. It creates a simple and intuitive interface for fast and simple programming of the layout.

The IIoT and digital twin can automate the system and put the building blocks for smart RMS. We can collect and store data from all platforms in real-time, which we can use to train machine learning algorithms to classify and predict the RMS. We can implement reinforcement learning and image recognition to create self adaptable control system for the robots. At the same time, we can apply image recognition models to detect when prints are failing or any other failure in the RMS.

Industry 4.0 technologies have enhanced the flexibility and reconfigurability of manufacturing systems by integrating robots, additive manufacturing, digital technologies, and smart RMS. However, we have several challenges that the proposed RMS is still facing.

The first challenge is to arrange the layout of the system in such a way that considering the limited working area of the robot arms. Currently, we address this challenge by simulation through a digital twin. However, we need to find a better solution to solve this problem autonomously. The second challenge is that the mobile robot needs extra force to move the trolleys and often ends up spinning while moving the platforms. In addition, if one of the ten wheels gets stuck, it will dramatically reduce the accuracy and cause collisions with other platforms. As a better solution, we can remove all wheels of the platforms and use a mobile robot with high lifting capacity. Then the mobile robot would be able to lift the platform and place them in different positions. Regardless of these challenges, the system has a unique characteristic that can not only be reconfigured in different layouts but can also be rearranged in other locations irrespective of the manufacturing space.

We also proposed WPT systems to electrify the platforms and increase the flexibility of the manufacturing system. In addition, we can utilize static or dynamic WPT to electrify the system. The dynamic WPT can electrify both the platforms and the mobile robot, increasing the system's extent and cost. In contrast, static WPT offers a good option to electrify the platforms from each other or a main fixed machine. The system will get better efficiency by correcting the misalignment between the platforms.

6. Conclusion

We have proposed a number of industry 4.0 technologies to build an highly flexible RMS. We also expand the industry 4.0 technologies principle by adding WPT. The WPT system increases the flexibility and reliability of the proposed RMS. Our system includes five platforms containing robot arms, a conveyor belt, a conveyor lift, and a 3D printer. We have retrofitted the platforms and used a mobile robot to reconfigure the platforms automatically. Then, we created a simulation model that controls and arranges the platforms using the digital twin to configure the system. The simulation model has the same scale and coordinates as the mobile robot. Using the OPC UA server, we send the coordinates of the platforms from the simulation model to the physical model. In addition, we present two demonstrations: the first simulation showing the system's flexibility with the production and assembly of a box, and the second simulation showing how the mobile robot can reconfigure the platforms based on the simulation model.

7. Future works

The proposed system can be further expanded and automated.

7.1. Automatic layout design

As can be seen from the simulation results, there are multiple solutions for positioning the platforms. Therefore, optimizing the layout with the shortest path or smallest area can reduce manufacturing time and costs. We seek to develop a mathematical model that can find a sub-optimal layout for a system with multiple platforms as further work. With the mathematical model, the system will rearrange the layout automatically depending on what we need to manufacture.

7.2. Automatic programming/control

Another challenge facing the system is to control and program the platforms automatically. Due to the mobile robot inaccuracy, the platforms aren't positioned with high accuracy. Therefore, using pre-programmed programs on the robot arms will not be feasible. Besides, the literature has previously shown that manually controlling, programming, and setting up the system is time-consuming, requiring expertise in control systems [5]. We will investigate and create a system that can be programmed automatically depending on what will be manufactured.

7.3. Wireless electrification of RMS

Finally, we will study in detail different approaches of WPT and examine capacitive power transfer (CPT) as a low-cost solution for powering the RMS. In addition, we expand the system with a mobile battery platform that can power other platforms using CPT.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Fathi M, Ghobakhloo M. Enabling mass customization and manufacturing sustainability in industry 4.0 context: a novel heuristic algorithm for in-plant material supply optimization. Sustainability 2020;12(16).
[2] Koren Y, Shpitalni M. Design of reconfigurable manufacturing systems. J Manuf Syst 2010;29(4):130–41. https://doi.org/10.1016/j.jmsy.2011.01.001.
[3] Malik AA, Masood T, Kousar R. Reconfiguring and ramping-up ventilator production in the face of covid-19: Can robots help? J Manuf Syst 2021;60:864–75.
[4] Koren Y, Heisel U, Jovane F, Moriwaki T, Pritschow G, Ulsoy G, et al. Reconfigurable manufacturing systems. CIRP Ann 1999;48(2):527–40. https://doi.org/10.1016/S0007-8506(07)63232-6.
[5] Kim DY, Park JW, Baek S, Park KB, Kim HR, Park JI, et al. A modular factory testbed for the rapid reconfiguration of manufacturing systems. J Intell Manuf 2020;31(3):661–80. https://doi.org/10.1007/s10845-019-01471-2.
[6] Putnik G, Sluga A, ElMaraghy H, Teti R, Koren Y, Tolio T, et al. Scalability in manufacturing systems design and operation: state-of-the-art and future developments roadmap. CIRP Ann 2013;62(2):751–74. https://doi.org/10.1016/j.cirp.2013.05.002. ⟨https://www.sciencedirect.com/science/article/pii/S0007850613001923⟩.
[7] Klingenberg CO, Borges MAV, Antunes Jr JAV. Industry 4.0 as a data-driven paradigm: a systematic literature review on technologies. J Manuf Technol Manag 2021;32(3, SI):570–92. https://doi.org/10.1108/JMTM-09-2018-0325.
[8] Singh A, Gupta P, Asjad M. Reconfigurable manufacturing system (rms): Accelerate towards industries 4.0. Proc Int Conf Sustain Comput Sci, Technol Manag (SUSCOM) 2019;01. https://doi.org/10.2139/ssrn.3354485.
[9] Bortolini M, Galizia FG, Mora C. Reconfigurable manufacturing systems: Literature review and research trend. J Manuf Syst 2018;49:93–106. https://doi.org/10.1016/j.jmsy.2018.09.005. ⟨https://www.sciencedirect.com/science/article/pii/S0278612518303650⟩.
[10] Maganha I, Silva C, Ferreira LMDF. The layout design in reconfigurable manufacturing systems: a literature review. Int J Adv Manuf Technol 2019;105 (1–4):683–700. https://doi.org/10.1007/s00170-019-04190-3.
[11] Morgan J, Halton M, Qiao Y, Breslin JG. Industry 4.0 smart reconfigurable manufacturing machines. J Manuf Syst 2021;59:481–506. https://doi.org/10.1016/j.jmsy.2021.03.001.
[12] H. Arnarson, B. Solvang, 2022. Reconfigurable autonomous industrial mobile manipulator system, in: 2022 IEEE/SICE International Symposium on System Integration (SII), 2022, 772–777.10.1109/SII52469.2022.9708887.
[13] D. Sanderson, J. C. Chaplin, L. De Silva, P. Holmes, S. Ratchev, 2016. Smart manufacturing and reconfigurable technologies: Towards an integrated environment for evolvable assembly systems, in: 2016 IEEE 1st International Workshops on Foundations and Applications of Self* Systems (FAS*W), 2016, 263–264.10.1109/FAS-W.2016.61.
[14] SMC, SMC International Training – The didactic division of SMC Corporation, [Online; accessed 3. Feb. 2022] (Feb 2022). ⟨https://www.smctraining.com⟩.
[15] Madsen O, Møller C. The aau smart production laboratory for teaching and research in emerging digital manufacturing technologies. Procedia Manuf 2017;9: 106–12. https://doi.org/10.1016/j.promfg.2017.04.036. 7th Conference on Learning Factories, CLF 2017.
[16] daCunha C, Cardin O, Gallot G, Viaud J. Designing the digital twins of reconfigurable manufacturing systems: application on a smart factory. IFAC-Pap 2021;54(1):874–9. https://doi.org/10.1016/j.ifacol.2021.08.103. 17th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2021.
[17] U. of Wisconsin, IMS Centre Laboratories | Intelligent Manufacturing Systems (IMS) Centre, [Online; Accessed 2. Feb. 2022] (Feb 2022). ⟨https://www.uwindsor.ca/intelligent-manufacturing-systems/299/ims-centre-laboratories⟩.
[18] N. Jäpel, Industrie 4.0 Modellfabrik, [Online; accessed 2. Feb. 2022] (Feb 2022). https://www.htw-dresden.de/hochschule/fakultaeten/info-math/forschung/smart-production-systems/industrie-40-modellfabrik.
[19] Festo, CP Factory - The Cyber-Physical Factory, [Online; accessed 5. Feb. 2022] (Feb 2022). ⟨https://www.festo-didactic.com/int-en/learning-systems/learning-factories,cim-fms-systems/cp-factory/cp-factory-the-cyber-physical-factory.htm?fbid=aW50LmVuLjU1Ny4xNy4xOC4xMjkzLjc2NDM⟩.
[20] Adamietz R, Giesen T, Mayer P, Johnson A, Bibb R, Seifarth C. Reconfigurable and transportable container-integrated production system. Robot Comput-Integr Manuf 2018;53:1–20. https://doi.org/10.1016/j.rcim.2018.02.008. ⟨https://www.sciencedirect.com/science/article/pii/S0736584517301515⟩.
[21] Kang HS, Noh SD, Son JY, Kim H, Park JH, Lee JY. The FaaS system using additive manufacturing for personalized production. RAPID Prototyp J 2018;24(9): 1486–99. https://doi.org/10.1108/RPJ-11-2016-0195.
[22] H. Cheng, H. Chen, Y. Liu, Object handling using autonomous industrial mobile manipulator, in: 2013 IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems, 2013, 36–41.10.1109/CYBER.2013.6705416.
[23] Hvilshoj M, Bogh S, Nielsen OS, Madsen O. Autonomous industrial mobile manipulation (AIMM): past, present and future. Ind ROBOT- Int J Robot Res APPLICATION 2012;39(2):120–35. https://doi.org/10.1108/01439911211201582.
[24] Inoue S, Urata A, Kodama T, Huwer T, Maruyama Y, Fujita S, et al. High-precision mobile robotic manipulator for reconfigurable manufacturing systems. Int J Autom Technol 2021;15(5):651–60. https://doi.org/10.20965/ijat.2021.p0651.
[25] Andersen RE, Hansen EB, Cerny D, Madsen S, Pulendralingam B, Bøgh S, et al. Integration of a skill-based collaborative mobile robot in a smart cyber-physical environment. Procedia Manuf 2017;11:114–23. https://doi.org/10.1016/j.promfg.2017.07.209. 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017, 27-30 June 2017, Modena, Italy.
[26] Singh A, Gupta S, Asjad M, Gupta P. Reconfigurable manufacturing systems: journey and the road ahead. Int J Syst Assur Eng Manag 2017;8(2, 2):1849–57. https://doi.org/10.1007/s13198-017-0610-z.
[27] Khanna K, Kumar R. Reconfigurable manufacturing system: a state-of-the-art review, BENCHMARKING-AN. Int J 2019;26(8):2608–35. https://doi.org/10.1108/BIJ-05-2018-0140.
[28] R. Pansare, G. Yadav, M.R. Nagare, Reconfigurable manufacturing system: a systematic review, meta-analysis and future research directions, JOURNAL OF ENGINEERING DESIGN AND TECHNOLOGY 10.1108/JEDT-05–2021-0231.
[29] Song C, Ding Y, Eid A, Hester JGD, He X, Bahr R, et al. Advances in wirelessly powered backscatter communications: From antenna/rf circuitry design to printed

flexible electronics. Proc IEEE 2022;110(1):171–92. https://doi.org/10.1109/JPROC.2021.3125285.
[30] Psomas C, You M, Liang K, Zheng G, Krikidis I. Design and analysis of swipt with safety constraints. Proc IEEE 2022;110(1):107–26. https://doi.org/10.1109/JPROC.2021.3130084.
[31] Qu X, Zhang W, Wong S-C, Tse CK. Design of a current-source-output inductive power transfer led lighting system. IEEE J Emerg Sel Top Power Electron 2015;3(1):306–14. https://doi.org/10.1109/JESTPE.2014.2318045.
[32] Jiang C, Chau KT, Leung YY, Liu C, Lee CHT, Han W. Design and analysis of wireless ballastless fluorescent lighting. IEEE Trans Ind Electron 2019;66(5):4065–74. https://doi.org/10.1109/TIE.2017.2784345.
[33] Han W, Chau KT, Jiang C, Liu W, Lam WH. High-order compensated wireless power transfer for dimmable metal halide lamps. IEEE Trans Power Electron 2020;35(6):6269–79. https://doi.org/10.1109/TPEL.2019.2950206.
[34] Han W, Chau KT, Zhang Z. Flexible induction heating using magnetic resonant coupling. IEEE Trans Ind Electron 2017;64(3):1982–92. https://doi.org/10.1109/TIE.2016.2620099.
[35] Zhang Y, Yang J, Jiang D, Li D, Qu R. Design, manufacture, and test of a rotary transformer for contactless power transfer system. IEEE Trans Magn 2022;58(2):1–6. https://doi.org/10.1109/TMAG.2021.3094135.
[36] Zhang Z, Chau KT, Qiu C, Liu C. Energy encryption for wireless power transfer. IEEE Trans Power Electron 2015;30(9):5237–46. https://doi.org/10.1109/TPEL.2014.2363686.
[37] Zeng Y, Rong C, Lu C, Tao X, Liu X, Liu R, et al. Misalignment insensitive wireless power transfer system using a hybrid transmitter for autonomous underwater vehicles. IEEE Trans Ind Appl 2022;58(1):1298–306. https://doi.org/10.1109/TIA.2021.3110496.
[38] Wang D, Cui S, Zhang J, Bie Z, Song K, Zhu C. A novel arc-shaped lightweight magnetic coupler for auv wireless power transfer. IEEE Trans Ind Appl 2022;58(1):1315–29. https://doi.org/10.1109/TIA.2021.3109839.
[39] Wu P, Xiao F, Huang H, Sha C, Yu S. Adaptive and extensible energy supply mechanism for uavs-aided wireless-powered internet of things. IEEE Internet Things J 2020;7(9):9201–13. https://doi.org/10.1109/JIOT.2020.3005133.
[40] Wei Z, Yu X, Ng DWK, Schober R. Resource allocation for simultaneous wireless information and power transfer systems: a tutorial overview. Proc IEEE 2022;110(1):127–49. https://doi.org/10.1109/JPROC.2021.3120888.
[41] Liu W, Chau KT, Lee CHT, Cao L, Han W. Wireless power and drive transfer for piping network. IEEE Trans Ind Electron 2022;69(3):2345–56. https://doi.org/10.1109/TIE.2021.3068675.
[42] Covic GA, Boys JT. Modern trends in inductive power transfer for transportation applications. IEEE J Emerg Sel Top Power Electron 2013;1(1):28–41. https://doi.org/10.1109/JESTPE.2013.2264473.
[43] Guidi G, Suul JA, Jenset F, Sorfonn I. Wireless charging for ships: High-power inductive charging for battery electric and plug-in hybrid vessels. IEEE Electrif Mag 2017;5(3):22–32. https://doi.org/10.1109/MELE.2017.2718829.
[44] Ahmad A, Alam MS, Chabaan R. A comprehensive review of wireless charging technologies for electric vehicles. IEEE Trans Transp Electrif 2018;4(1):38–63. https://doi.org/10.1109/TTE.2017.2771619.
[45] H. Arnarson, B. Solvang, 2022. Reconfigurable 3d printing platform for warehouses, in: 2022 6th International Conference on Green Technology and Sustainable Development (GTSD 2022), (Accepted), 2022, 772–777.
[46] H. Arnarson, 2022. Demonstration of production simulation, [Online; accessed 7. Feb. 2022] (Feb 2022). https://youtu.be/6ir7RUN_uk0.
[47] H. Arnarson, 2022. Super flexible reconfigurable manufacturing system (5x speed), [Online; accessed 21. Feb. 2022] (FEB 2022). https://youtu.be/UXUlaawd8Ps.
[48] H. Arnarson, 2022. Digital twin labratory using open access middleware for real-time communication and cooperation, [Online; Accessed 24. Mar. 2022] (MAR 2022). https://www.youtube.com/watch?v=HXskVx1IVyg.
[49] H. Arnarson, B. A. Bremdal, B. Solvang, 2022. Reconfigurable manufacturing: Towards an industrial big data approach, in: 2022 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), (Accepted), 2022.
[50] ITU-R Recommendation ITU-R SM.2110, Frequency ranges for operation of non-beam wireless power transmission systems, Available at ⟨https://www.itu.int/rec/R-REC-SM.2110–0-201709-S⟩ (2021/ 11/09).
[51] M. I. Robots, 2022. Mobile robot from mobile industrial robots - mir100, [Online; accessed 27. Jan. 2022] (Jan 2022). https://www.mobile-industrial-robots.com/solutions/robots/mir100.
[52] O. Foundation, Unified architecture, [Online; accessed 04. Feb. 2022].⟨https://opcfoundation.org/about/opc-technologies/opc-ua/⟩.
[53] VanDerHorn E, Mahadevan S. Digital twin: Generalization, characterization and implementation. Decis Support Syst 2021;145:113524. https://doi.org/10.1016/j.dss.2021.113524.
[54] H. Arnarson, B. Solvang, B. Shu, 2020. The application of open access middleware for cooperation among heterogeneous manufacturing systems, in: 2020 3rd International Symposium on Small-scale Intelligent Manufacturing Systems (SIMS), 2020, 1–6.10.1109/SIMS49386.2020.9121537.
[55] Visual Components, Visual Components Premium - Visual Components, [Online; accessed 27. Jan. 2022] (Jan 2022). ⟨https://www.visualcomponents.com/products/premium⟩.

Paper 3

Reconfigurable 3D printing platform for warehouses

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Author's Contribution

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

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***Abstract*—The world is moving towards a more sustainable future where the focus is to reduce energy and resource consumption. Warehouses constitute a significant contributor to emissions in supply chains. At the same time, there has been little focus on the sustainability of warehouses. One method to reduce energy and resource consumption in warehouses is to reduce the size of warehouse buildings. This can be done by adding a manufacturing system inside the warehouse to reduce the number of parts being stored. For such a system to work, the manufacturing system needs to be flexible and produce multiple parts. This paper will investigate and demonstrate how a reconfigurable manufacturing system (RMS) with additive manufacturing (AM) can be implemented in a warehouse.**

***Index Terms*—Reconfigurable Manufacturing System (RMS), Mobile robots, Warehousing, Additive Manufacturing (AM), Mobile 3D printing**

I. Introduction

As global political conversation prioritizes moving towards a sustainable future with low carbon emissions. One area where there has been limited focus on sustainability is warehousing. At the same, warehousing is a sizable contributor to emissions in supply chains [1].

A strategy to make warehouses more sustainable is to reduce the size of warehouse buildings. The warehouse buildings are the most significant contributor to natural resources and energy consumption [2]. One approach to reduce the size of a warehouse is to add a manufacturing system as a part of the warehouse. A warehouse with spear parts can reduce the number of parts by having a manufacturing system that can produce the parts when needed.

However, such a manufacturing system needs to be flexible and capable of producing multiple products. Using a reconfigurable manufacturing (RMS) system can be a good option.

RMS is built on modularity, where the manufacturing system can rapidly change the functionality and production volume [3]. The idea of an RMS is to be able to manufacture as a dedicated manufacturing system (DMS) with the flexibility of a flexible manufacturing system (FMS) [3].

To combine an RMS and warehouse, there is a need for industry 4.0 technologies such as internet of things (IoT), cyber physical systems (CPS), advanced robotics, etc. Within academia, little research has been done on implementing industry 4.0 technologies in RMS [4, 5]. Using industry 4.0 technologies with an RMS is essential for the success of RMS [5] and combining for example additive manufacturing (AM) with RMS can improve the flexibility and agility of the system.

A part of the warehouse can include an RMS with AM to manufacture parts on demand. This can reduce warehouses' size since parts can be stored digitally and printed/manufactured when needed. To the authors' knowledge, there is no investigation of using an RMS in a warehouse.

In this paper, we will investigate how RMS with AM can be combined and used in warehouses to increase automation and reduce the size of the warehouse. We will also demonstrate how a mobile 3D printer solution, where a mobile robot distributes printers to a warehouse and manufacturing system when and where needed.

The contributions of this work are as follows:

1) Investigates the potential of an RMS with AM in warehouses.
2) Overview of the current state of AM, RMS with AM, and flexible AM systems.
3) Propose a mobile 3D printer solution, as part of an RMS system for automatic printing and refill in warehouses.

The rest of the paper is organized as follows; Section II investigates the potential to implement RMS and AM into warehouses. Section III presents previous studies on RMS and AM. Then in Section IV, we present a mobile 3D printer that can be used in warehouses and manufacturing systems and the results in Section V. Finally, conclusion and further work in section VI.

II. RMS with static warehouse storage

The concept and practice of warehousing date back many decades. Among the first recollections of warehousing is the storage of grain by Joseph of Genesis [6]. In religious scripture, it is noted how useful this storage practice turned out to be, as it helped many Egyptians later when famine spread across the land.

Today, warehousing is practiced across many industries – manufacturing, agriculture, e-commerce, and retail being just a few examples. The common feature of these industries' use of warehousing is that it seems vital. A potential scenario where warehousing is superfluous is considered unrealistic and excessively ambitious. From an item's production phase to its shipment to stores and customers, there is usually a phase in-between where the item must be placed in the company's storage until a customer orders the item. This phase is, according to most of today's production practices, inevitable.

As the global focus on sustainability and environmental friendliness increases, a production system that produces only what is certain to be sold to customers should be of interest to all industries. In the case of more industries adopting RMS practice, the hitherto inevitable practice of warehousing could be scaled down significantly. In addition to the sustainability aspect, there is also the financial component – with no warehousing, overall costs would decrease.

However, opposite trends have also been observed. The e-commerce industry's expansion into mass customization has in some cases led to an increased demand for warehouse storage space [2]. This especially seems to be the case for business-to-consumer markets. With increased opportunities for online purchases across fields, customer demand has become more persistent than ever before and can safely be assumed to be uninterrupted [2]. In industries such as retail, this results in a need for warehouse storage, as the products are manufactured prior to being marketed. The pre-production and storage of the products allow the companies to ship the products to customers as soon as possible after the order has been placed.

Thus far, little research has been conducted on RMS technology's effect on warehousing. This particularly holds true for business-to-business markets [7]. In industries such as the energy or petroleum industries, there is a certain level of predictability in demand for new products after decades of experience at this stage. For such industries, a solution combining AM of products with a RMS may lead to a decreased demand for warehouses where products and spare parts are stored for long periods.

The potential removal of the warehousing stage would cause a change to the supply chain as known today. Such a change would be of great interest to companies, largely due to the decreased costs it would result in. Companies spend significant amounts on warehousing, which causes it to be one of the most expensive components of the supply chain [2].

Furthermore, with more companies and industries becoming aware of the importance of reducing carbon emissions on a global scale, it is now also of great interest to reduce warehousing activities and costs for the purpose of sustainable practice. As such, decreased overall costs for a company can be observed to be directly related to a reduced number of activities [8]. Other than costs, it is also observed to be a trend among customers, both in business-to-consumer markets and business-to-business markets, to prefer companies that actively prioritize sustainable operations [2].

In cases where the warehouse stage cannot be removed entirely from the supply chain, an RMS system would still hold the potential of decreasing warehouse space. This could especially be the case for industries in which orders are sparse and order predictability is significant. Products could be produced and stored in the same space, as the probability of the need for storage would be less. In a situation where only necessary products are manufactured through AM and required to be shipped immediately afterwards, the need for additional storage space is less.

III. Previous studies

This section presents the current state of 3D printing in the manufacturing industry and how it has been used with a RMS systems.

3D printing or Additive manufacturing is a manufacturing technology defined by the ASTM society as a *"process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative manufacturing methodologies"*[9]. Although 3D printing was formally introduced almost three decades ago, it is only in recent years that the interest in 3D printing has exploded. The rapid technological advancement of 3D printing and continuous growing attentiveness brings us to the verge of a new paradigm shift in manufacturing.

3D printing is a flexible production process that requires minimal setup as compared to traditional processes, and despite only being in the early phase of adoption shows signs of delivering great environmental benefits. Such an increase material efficiency, reduction of waste, lowers the carbon footprint through localized production and less transportation, and eliminates or reduces the needs for inventories[10].

It was initially a technique solely used for rapid prototyping. However, as the technology has matured, so have the applications. Nowadays, we see that AM has unlocked new opportunities with more and more turning towards 3D printing for larger industrial production and even for mass customization.

Mass customization is the capability offered by firms to provide product variety and customization on a large scale[11], and is not something that is easily achievable as it requires a highly flexible production technology. 3D printing and mass customization has been an area of interest for researchers for some time already but is not something that is widely applied so far.

Although 3D printing offer benefits such as increased design freedom, tool-less production and high flexibility[12] that easily has the potential to address individual customers product desire and lead to mass customization it alone have not really been able to penetrate the manufacturing industry. However, by using 3D printing in the right manufacturing environment such as an RMS, it could expedite firms journey towards achieving mass customization at a wider scale.

There are only a select few studies on using 3D printers as a part of the manufacturing for RMS. One example is a modular manufacturing system [13]. This system consists of a 3D printer, post-processing, assembly, inspection and packing modules. The 3D printer is used to achieve variety, allowing the system to achieve personalized or mass customization in manufacturing. The paper notes that current research has mainly focused on 3D printers itself and creating service models on using it. However, making 3D printers a valid manufacturing method requires a more advanced 3D printing model supported by digital technologies.

A second example is given by Adam [14], where a 3D printer has been added to a RMS. In their study, a miniature manufacturing system inside a movable container was built, including a module with a thermoplastic material extrusion printer. The system was made to manufacture parts with a high level of customization. Further the container could be moved where the parts are needed and the just- in- time principle could be applied.

One of the limitations of AM systems is that most 3D printers are stationary, causing isolation, making it difficult to combine different technologies and overcome limitations of the individual processes [15].

There are examples of mobile robots that can 3D print on the floor with plastic [16, 17, 18] and concrete [19, 20, 21]. These systems utilize one or more mobile robots to 3D print objects in a flexible manner. Since mobile robots are used, the systems can print large parts in any given location. One of the problems with printing on the floor is that the quality of the product is low. If the floor is dirty, uneven, or an object on the floor can damage the 3D printed part. In addition, the mobile robot positioning isn't that accurate, which further reduces the quality of the 3D printed part.

IV. Modular 3D printer system

Based on the previous chapters, a demonstration has been developed to demonstrate how the concept of RMS and AM can be used in warehouses. The idea is to have a system that can automatically move a 3D printer in a warehouse and print parts without human intervention.

A system has been created to showcase how a mobile 3D printer platform can work. The system has been limited to plastic printing, for simplicity and since the technology is quite mature and in wide usage.

A. System setup

One approach that can be used is the autonomous industrial mobile manipulators (AIMM). The AIMM uses a mobile robot to transport a robot arm between workstations. In the previous study [22], an AIMM was split into two parts to increase the utilization of the robot arm and mobile robot. The same AIMM principle from [22] can be used to create a mobile 3D printer. In this case, the robot arm is replaced with a 3D printer.

The system has been made to be automatic without human labor. Most of the 3D printers on the market today use vertical printers. When these printers are done printing, a human needs to pick the part of the printer and might risk damaging the part when removing it.

A different type of printer is a conveyor-based 3D printer. These printers print at a 45-degree angle onto a conveyor. By printing on a conveyor, the printer can print parts where there is no restriction on the z-axis (endless). In addition, printing on the conveyor allows for automatic removal of printed parts. After each print, the 3D printer can move the part of the conveyor.

Therefore, a Creality CR-30 [23] conveyor printer is used. It can print parts with dimensions of 200x170x∞ mm. The mobile 3D printing platform is fitted with the 3D printer and consists of six main parts:

1) **3D printer:** For automatic 3D printing and removal of parts.
2) **Raspberry Pi:** The main computer for the platform is a raspberry pi
3) **Batteries:** Two 12v batteries are used to power the platform
4) **Voltage converter:** Used to convert the 12v DC from the batter to 230v AC for the 3d printer
5) **Movable marker:** A marker on a linear actuator is placed in front of the platform, for automatic pickup of the mobile robot.
6) **Mobile robot:** The mobile robot is used to transport the 3D printer

The platform is fitted with five 12V batteries connected in parallel. Since the 3D printer uses 230V, a voltage converter is needed to convert from 12 DC to 230V AC. Figure 1 shows the platform and the six components.

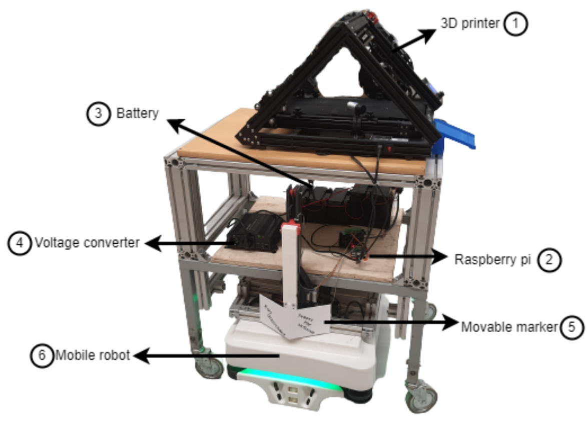

Fig. 1. The six main parts of the platform. (1) 3D printer, (2) Raspberry Pi, (3) Batteries, (4) Voltage converter, and (5) Movable marker (6) Mobile robot.

A mobile robot (MiR100) is used to transport and place the 3D printer. As can be seen in figure 1, there is a movable marker. This marker is used to increase the positioning accuracy of the mobile robot. Using the marker allows the mobile robot to place and pick up the platform anywhere in the environment. A video demonstrating the docking and undocking of the platform can be seen at https://youtu.be/RtOX0HGiqRs.

B. Communication and control

There is a need for communication between all parts in the system. For simple and reliable communication between the different parts, the Open Platform Communication Unified Architecture (OPC UA) [24] standard is used. The OPC UA standard is an IEC 62541 standard used for industrial communication [25]. In this system, the OPC UA server is used as a bridge to create communication between the mobile robot, 3D printer and control computer, as can be seen in figure 2.

For control of the 3D printer, OctoPrint [26] is used. OctoPrint is an open-source web server that allows the user to control 3D printers remotely [27]. A python API can be used to start and stop prints, monitor the printer and collect data. A python program is created which connects control functions in OctoPrint to the OPC UA server. It is possible to start prints and monitor the printer remotely with the OPC UA server.

As can be seen in figure 2, the main control system is the manufacturing processes management (MPM). The MPM is used to tell where the mobile robot should drive and what the 3D printer will print. The idea is that an enterprise resource planning (ERP) system or warehouse management (WM) system, sends an order to the MPM system. Then the MPM will order the mobile robot to transport it to the required place and the 3D printer will start to produce parts.

An example of such a case can be if the WM system notices that it is almost empty of a part, it can send an order to the MPM for a refill of parts. Then the MPM system orders the mobile robot to transport the 3D print platform and the printer will start to produce parts.

C. Demonstration

To showcase how the system works a video demonstration is created. The demonstration shows two example use cases, one for just-in-time production with a CNC machine and the second example in refill of parts. The video can be found at https://youtu.be/Z6WQe1bf648.

In the video, the 3D printer starts producing a part and automatically ejects it to the manufacturing system. The mobile robot picks up the 3D printer platform and transports it to storage shelves. Then the 3D printer prints a different part to show automatic refill of storage. Afterward, the mobile robot will pick the 3D printer again and move it to an assembly station and the 3D printer starts to print parts.

V. Discussion

Large warehouses use a lot of resources and energy and it can be beneficial to implement a manufacturing system inside a warehouse to reduce the overall size of the warehouse building. Combining RMS with AM allows such warehouse manufacturing system to become more flexible and automated.

One disadvantage of our mobile 3D printer system is that the platform has wheels. It can lead to an unstable platform that can reduce the quality of printed objects. A proposed solution would be to remove the wheels of the platform. Instead of pulling the platform, it can be lifted up by the mobile robot and rigidly placed where it is needed. Additionally, the system faces a calibration challenge as the accuracy of the 3D printer may be compromised during relocation.

However, this is a very flexible system and the mobile robot is able to transport the 3D printer to any position in the environment. In addition, having a conveyor 3D printer allows for continuous 3D printing without any human intervention.

Despite these strengths, the study does face certain limitations. Further investigation is required to determine which parts are most suitable for printing within this system. Additionally, the potential impact on the printer's accuracy caused by frequent transportation remains a subject of concern that necessitates additional scrutiny.

It should be noted that 3D printers are currently slow production methods. If the parts are large, the manufacturing process is very slow. However, if the parts are small, they can be produced much quicker. It is possible to add more 3D printers to scale up the production volume. In addition, 3D printers can work almost without human intervention, 24 hours a day.

VI. Conclusion and further work

In this paper, we have introduced emerging industry 4.0 technologies, such as AM with RMS, as part of a warehouse manufacturing system. This system can manufacture parts on demand, instead of storing all parts. This can reduce the size of the warehouse, which is of crucial importance in a sustainability perspective.

We have proposed a mobile 3D printer platform that can be used for automatic refilling. The system includes a conveyor 3D printer that allows for automatic removal of parts. The system can be controlled automatically through the use of the OPC UA server and an MPM control program is used to control the production of parts.

A. Further research and challenges

A small-scale system is developed in this paper to showcase how RMS and AM can be used in a warehouse. However, there are still many challenges that need further research.

1) Expanding the Warehouse with RMS: The extent to which significant warehouse reduction or elimination is possible when using an RMS system, should be tested and modeled in order to gain perspective on whether such a concept is achievable in reality. Also, it would be of interest to see a modeling of an RMS factory and warehouse combined, in literature. A successful example of this would be of great interest to industry, as it would have the potential to decrease costs relating to supply chain activities. Exemplifications of the theories presented in this paper would be of use to observe the exact potential of this.

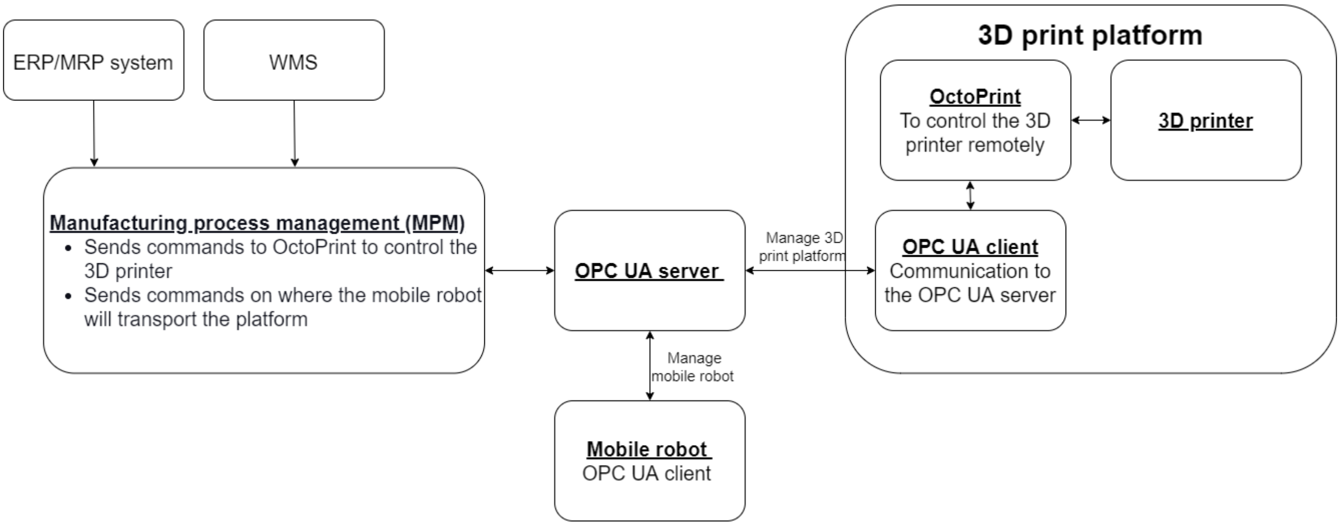

Fig. 2. How the system is connected together

2) Supply chain distribution: The convergence of technological innovations within Industry 4.0 is resulting in many new promising solutions. The reconfigurable 3D printing platform is an example where different Industry 4.0 solutions such as IoT, autonomous robotics, and 3D printing converge, which can bring disruptive transformation to entire supply chains. To further understand the effect and applicability of this system it would be highly beneficial to look at how the supply chain can be affected by the reconfigurable 3D printing platform.

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REFERENCES

[1] Alessio Ishizaka et al. "Sustainable warehouse evaluation with AHPSort traffic light visualisation and post-optimal analysis method". In: *Journal of the Operational Research Society* 73.3 (2022), pp. 558–575. DOI: 10.1080/01605682.2020.1848361. eprint: https://doi.org/10.1080/01605682.2020.1848361. URL: https://doi.org/10.1080/01605682.2020.1848361.

[2] Maicol Bartolini, Eleonora Bottani, and Eric H. Grosse. "Green warehousing: Systematic literature review and bibliometric analysis". In: *Journal of Cleaner Production* 226 (2019), pp. 242–258. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2019.04.055. URL: https://www.sciencedirect.com/science/article/pii/S0959652619311321.

[3] Yoram Koren and Moshe Shpitalni. "Design of reconfigurable manufacturing systems". In: *Journal of Manufacturing Systems* 29.4 (2010), pp. 130–141. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2011.01.001. URL: https://www.sciencedirect.com/science/article/pii/S0278612511000021.

[4] Marco Bortolini, Francesco Gabriele Galizia, and Cristina Mora. "Reconfigurable manufacturing systems: Literature review and research trend". In: *Journal of Manufacturing Systems* 49 (2018), pp. 93–106. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2018.09.005. URL: https://www.sciencedirect.com/science/article/pii/S0278612518303650.

[5] Ashutosh Singh, Piyush Gupta, and Mohammad Asjad. "Reconfigurable Manufacturing System (RMS): Accelerate Towards Industries 4.0". In: *SSRN Electronic Journal* (Jan. 2019). DOI: 10.2139/ssrn.3354485.

[6] J. Moffatt. *The Bible: James Moffatt Translation*. Kregel Publications, 2004. ISBN: 978-0-82543228-6. URL: https://books.google.no/books/about/The_Bible.html?id=oZfnVGt4j7MC&redir_esc=y.

[7] K.H. Leung, Carman K.M. Lee, and K.L. Choy. "An integrated online pick-to-sort order batching approach for managing frequent arrivals of B2B e-commerce orders under both fixed and variable time-window batching". In: *Advanced Engineering Informatics* 45 (2020), p. 101125. ISSN: 1474-0346. DOI: https://doi.org/10.1016/j.aei.2020.101125. URL: https://www.sciencedirect.com/science/article/pii/S147403462030094X.

[8] Zhengyi Li and Jiangtao Hai. "Inventory management for one warehouse multi-retailer systems with carbon emission costs". In: *Computers & Industrial Engineering* 130 (2019), pp. 565–574. ISSN: 0360-8352. DOI: https://doi.org/10.1016/j.cie.2019.03.015. URL: https://www.sciencedirect.com/science/article/pii/S0360835219301524.

[9] *ISO/ASTM:52900-2021(en), Additive manufacturing — General principles — Fundamentals and vocabulary*. URL: https://www.iso.org/standard/74514.html.

[10] Simon Ford and Mélanie Despeisse. "Additive manufacturing and sustainability: an exploratory study of the advantages and challenges". In: *Journal of Cleaner Production* 137 (2016), pp. 1573–1587. ISSN: 0959-6526. DOI: https://doi.org/10.1016/j.jclepro.2016.04.150. URL: https://www.sciencedirect.com/science/article/pii/S0959652616304395.

[11] B Joseph Pine and Stan Davis. "Mass customization: the new frontier in business competition". In: (1993).

[12] Rachel Lacroix, Ralf W. Seifert, and Anna Timonina-Farkas. "Benefiting from additive manufacturing for mass customization across the product life cycle". In: *Operations Research Perspectives* 8 (2021), p. 100201. ISSN: 2214-7160. DOI: https://doi.org/10.1016/j.orp.2021.100201. URL: https://www.sciencedirect.com/science/article/pii/S2214716021000208.

[13] Hyoung Seok Kang et al. "The FaaS system using additive manufacturing for personalized production". In: *RAPID PRO-*

TOTYPING JOURNAL 24.9 (2018), 1486–1499. ISSN: 1355-2546. DOI: {10.1108/RPJ-11-2016-0195}.

[14] Raphael Adamietz et al. “Reconfigurable and transportable container-integrated production system”. In: *Robotics and Computer-Integrated Manufacturing* 53 (2018), pp. 1–20. ISSN: 0736-5845. DOI: https://doi.org/10.1016/j.rcim.2018.02.008. URL: https://www.sciencedirect.com/science/article/pii/S0736584517301515.

[15] Lucas Galvan Marques, Robert Austin Williams, and Wenchao Zhou. “A Mobile 3 D Printer for Cooperative 3 D Printing”. In: 2017.

[16] Jace McPherson and Wenchao Zhou. “A chunk-based slicer for cooperative 3D printing”. In: *RAPID PROTOTYPING JOURNAL* 24.9 (2018), 1436–1446. ISSN: 1355-2546. DOI: {10.1108/RPJ-07-2017-0150}.

[17] Xuchu Xu, Ziteng Wang, and Chen Feng. *Projector-Guided Non-Holonomic Mobile 3D Printing*. 2021. arXiv: 2105.08950 [cs.RO].

[18] Jianran Lv, Hongyao Shen, and Jianzhong Ian. “Large-scale 3D printing technology based on the visual stitching method”. In: *RAPID PROTOTYPING JOURNAL* 25.7 (AUG 12 2019), 1232–1240. ISSN: 1355-2546. DOI: {10.1108/RPJ-03-2019-0059}.

[19] Julius Sustarevas et al. “MAP - A Mobile Agile Printer Robot for on-site Construction”. In: *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. 2018, pp. 2441–2448. DOI: 10.1109/IROS.2018.8593815.

[20] Andreas Sauter et al. “Development, implementation and optimization of a mobile 3D printing platform”. In: *PROGRESS IN ADDITIVE MANUFACTURING* 6.2 (MAY 2021), 231–241. ISSN: 2363-9512. DOI: {10.1007/s40964-020-00154-2}.

[21] Xu Zhang et al. “Large-scale 3D printing by a team of mobile robots”. In: *Automation in Construction* 95 (2018), pp. 98–106. ISSN: 0926-5805. DOI: https://doi.org/10.1016/j.autcon.2018.08.004. URL: https://www.sciencedirect.com/science/article/pii/S0926580518304011.

[22] Halldor Arnarson and Bjørn Solvang. “Reconfigurable autonomous industrial mobile manipulator system”. In: *2022 IEEE/SICE International Symposium on System Integration (SII)*. 2022, pp. 772–777. DOI: 10.1109/SII52469.2022.9708887.

[23] *Creality CR-30: The 3DPrintMill,Infinite-Z, Belt 3D Printer*. [Online; accessed 6. Mar. 2022]. Mar. 2022. URL: https://www.creality3dofficial.com/products/cr-30-infinite-z-belt-3d-printer.

[24] Peter Drahoš et al. “Trends in industrial communication and OPC UA”. In: *2018 Cybernetics Informatics (K I)*. 2018, pp. 1–5. DOI: 10.1109/CYBERI.2018.8337560.

[25] *Brochures - OPC Foundation*. [Online; accessed 21. Feb. 2022]. Sept. 2020. URL: https://opcfoundation.org/resources/brochures.

[26] Gina Häußge. *OctoPrint.org*. [Online; accessed 21. Feb. 2022]. Feb. 2022. URL: https://octoprint.org.

[27] Jiarui Xie et al. “Development of automated feature extraction and convolutional neural network optimization for real-time warping monitoring in 3D printing”. In: *INTERNATIONAL JOURNAL OF COMPUTER INTEGRATED MANUFACTURING* (). ISSN: 0951-192X. DOI: {10.1080/0951192X.2022.2025621}.

Paper 4

Towards automatic generation of image recognition models for industrial robot arms

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Author's Contribution

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

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***Abstract*—As the world moves towards mass customization, there is a need for a manufacturing system that can quickly adapt to market changes. Reconfigurable manufacturing systems (RMS) have been proposed as a solution. RMS is designed to be modular with a high degree of flexibility. However, such a structure creates a lot of complexity. For instance, if the modules are moved or changed, the robot arms in the system must be re-programmed. Adding 3D cameras and image recognition to the robot arms can solve some of these problems. Nevertheless, creating image recognition models is time-consuming work, requires human labor, and can increase the cost of manufacturing. To manufacture a large variety of products, there is a need to create image recognition models for each product. One method to automate the generation of image recognition models can be to use synthetic data. Synthetic data can be used to generate a large amount of labeled data, which can be used to train image recognition models.**

In this paper, we propose a method for training image recognition models using synthetic data, which can further automate robots in RMS. Specifically, the system utilizes a 3D model of a part to generate images, which are then processed by a cycle generative adversarial network (GAN) to enhance their realism. These images are subsequently auto-labeled and employed to train an image recognition model compatible with an industrial robot arm.

***Index Terms*—Industrial robot arm, Image recognition, Reconfigurable Manufacturing System (RMS), Cycle Generative Adversarial Network (GAN)**

I. Introduction

The manufacturing industry is transitioning from mass production towards mass customization, necessitating more frequent changes in manufacturing systems to accommodate new products and variations in demand [1]. Reconfigurable manufacturing systems (RMS) offer a solution to address these changes by providing modular manufacturing systems that can easily scale up or down and adapt to market fluctuations [2]. However, RMS still faces several challenges. For instance, RMS is designed to be reconfigurable at both the hardware and software levels [1], which requires the entire system and control software to be adjustable and flexible. Furthermore, the modular nature of RMS introduces additional complexity to the system [3], resulting in extended setup and programming times for manufacturing systems.

An example of an RMS featuring a modular structure is presented in [4]. This RMS employs a mobile robot to autonomously reconfigure the system's platforms without human intervention. A demonstration video of the system can be viewed at https://youtu.be/UXUlaawd8Ps. However, the system has a drawback: the mobile robot lacks accuracy when positioning the platforms that form the customized production line. Therefore, the robot arms in the system must be programmed for each reconfiguration. Given that RMS is designed for frequent reconfigurations, the robots and system require constant reprogramming, which is both time-consuming and demands robotics expertise. For future research, it is suggested to investigate how the system can be automatically programmed.

One approach that can automate the programming/control of the robot arms in an RMS is to use Industry 4.0 technologies. Industry 4.0 is the fourth industrial revolution which brings new technologies such as the internet of things (IoT), cyber-physical systems (CPS), big data and analytics, simulation and digital twin, artificial intelligence (AI) and additive manufacturing [5]. Singh et al. [6] note that Industry 4.0 technologies are essential for the future success of RMS.

One Industry 4.0 technology that can be used to automate the programming/control of the robot arms is to use AI with a bin-picking system. For example, using 3D cameras with image recognition to pick objects automatically. For example, robot arms equipped with 3D cameras and image recognition can classify objects and determine the distance [7]. Fujita et al. [8] looked at four state-of-the-art bin-picking solutions and investigated what technologies should be combined for effective bin-picking by robots. They found that in all the systems industrial robot arms were used because of their high accuracy and were combined with suction grippers and RGB-D sensors with CNN-based algorithms.

However, the challenge of using the CNN-based algorithms. In a typical machine learning project can be categorized into four steps, data collection, data labeling, model training, and deployment. One challenge is that the labeling step can consume up to 80% of development time [9]. Moreover, deep neural networks require substantial amounts of labeled data for training [10].

This relates to big data, which comprises four dimensions: volume, velocity, variety, and veracity. Volume relates to the amount of data, variety describes the types of data that are available, velocity is related to the speed at which the data is generated and the speed the data is processed, and veracity refers to the reliability (correctness) of the data [11].

Large, diverse, and accurate labeled datasets can be used to develop effective machine learning models. For image recognition, this entails capturing multiple images of an object from various angles, backgrounds, and lighting conditions. This process can be time-consuming, labor-intensive, and expensive, especially when considering the need to adapt to mass customization in manufacturing. Consequently, new machine learning models must be developed for each new product manufactured.

Therefore, to automate this process there is a need for a method to create data that can be used to train the machine learning model. One method that can be used to create training data, is generating synthetic data. Using synthetic data can give a cost-effective method to get large amounts of labeled training data [10].

One of the most used methods to generate synthetic data is generative adversarial networks (GAN) [10]. The GAN are neural networks that consist of two networks, one generator that generates the data and a discriminator. When the model is trained, the generator generates images, and the discriminator will try to identify which images are real and which are fake. The goal when training is to reach an equilibrium where the generated images follow the same distribution as the real images.

Generative Adversarial Networks (GANs) are a versatile class of neural networks that can be employed for a wide range of applications. For instance, Zou et al. [12] utilized GANs to enhance the calibration process of a welding robot, resulting in improved performance, while Mishra et al. [13] leveraged GANs for effective footstep planning in humanoid robots. However, a significant challenge associated with many GANs is the necessity for large datasets containing paired image-to-image translations, such as Pix2Pix [14]. Acquiring these datasets can be difficult and time-consuming.

To tackle this challenge, Zhu et al. [15] used another approach, namely, cycle GAN. Cycle GAN does not require paired images and is trained in an unsupervised manner. The cycle GAN uses two generators and two discriminators, and when training, the images are translated two times. One to translate the image, and a second time to translate the translated image back to the original image. Rao et al. [16] explored the use of cycle Generative Adversarial Networks (GAN) to make simulations more realistic. By using reinforcement learning, robot arms can be trained to pick objects automatically. However, the challenge lies in ensuring the simulation accurately reflects reality, which is where cycle GAN comes in, transforming simulated images to appear more realistic.

In the manufacturing of new products using CNC machines or additive manufacturing, CAD 3D models of the product are often readily available. These 3D models can be harnessed to create synthetic images for training machine learning algorithms. Building on this concept, Hanssen [17] designed a system that employs 3D models to generate images in various orientations, which were subsequently used to train a VGG16 model for image recognition. However, solely relying on the generated images with the VGG16 model [18] did not result in an effective image recognition system. Furthermore, Jordon et al. [10] highlight that the utilization of synthetic data remains an emerging research area, characterized by a scarcity of established frameworks for implementing the technology.

In this paper, we build upon Hanssen's work [17] by combining 3D models with a cycle GAN to create more realistic images and implementing YOLOv5, a fast and powerful image recognition model. We also propose a system structure detailing the necessary steps for creating an image recognition model from a 3D model.

The main contribution is to propose a novel method for automatically generating image recognition models for industrial robot arms in RMS, eliminating the need for reprogramming robots after system reconfigurations. Additionally, we showcase the practical implementation of this approach.

The rest of the paper is organized as follows: Section II proposes how the image recognition model can be generated from the 3D model and how the system works, and in Section III, experimental testing of the system is conducted. Then the paper discusses the results and concludes in Section IV and V.

II. A METHOD FOR GENERATING SYNTHETIC TRAINING DATA

This section presents a system for automatically generating image recognition models for 3D-printed parts. These models can then be seamlessly transferred to robot arm platforms, enabling the robot arms to directly utilize the image recognition models for object detection.

A. Generating synthetic data

The first step is to generate images from the 3D model. A Python program imports a 3D model as an STL file, rotates the model to different orientations and generates images from the model, as can be seen in Fig. 1. However, the resulting images may not resemble realistic 3D-printed parts. Therefore, it is necessary to further process and enhance the images to achieve a more lifelike appearance.

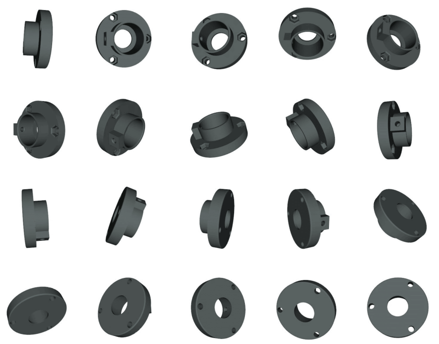

Fig. 1. The generated images of an STL file with different orientations.

B. Cycle GAN

As mentioned, the generated images do not have realistic features. One method that can be used to make the image look more realistic, is a translation system. The translation system can be used to generate new synthetic images based on real or synthetic images.

Therefore, cycle GAN is trained to translate the synthetic images from the 3D model into real-looking 3D printed parts. When training the cycle GAN, it was noted that if the generated images have white backgrounds, as shown in Fig. 1, the cycle GAN network will end up focusing on the background instead of the parts. Therefore, background images can be inserted into all the generated images for the training of the cycle GAN.

Moreover, filters can also be used. The idea of the filters is to slightly change the images with either a blur filter or by increasing or decreasing the brightness, sharpness, and contrast. If the filters made too big changes to the images, these filters would be added to the cycle GAN. However, small adjustments in the generated images would improve the translated images from the cycle GAN. Fig. 2, shows the images used to train the Cycle GAN.

a)

b)

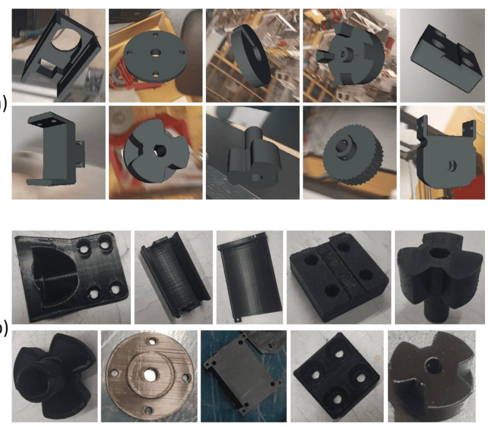

Fig. 2. The cycle GAN training approach: a) is the generated images, where backgrounds have been inserted, and b) is the real 3D printed parts used to train the cycle GAN.

In this study, we utilized 24 unique 3D models to generate a total of 2,700 synthetic images. The same 3D models were also 3D-printed and photographed, resulting in an additional 2,700 images. This provided us with a combined dataset of 5,400 images, comprising both generated and photographed images. Furthermore, we employed the code from [19] to implement the cycle GAN. The cycle GAN was tested on a 3D model not included in the training dataset, yielding the results illustrated in Fig. 3.

a)

b)

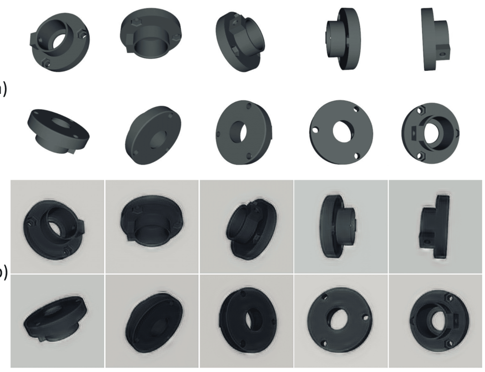

Fig. 3. The image shows the resulting cycle GAN, where a) The input images of the cycle GAN. b) The output from the cycle GAN.

C. Image recognition model

The You-Only-Look-Once (YOLO) object detection algorithm is known for its high accuracy and rapid processing capabilities, making it suitable for real-time applications [20]. By extracting the x and y coordinates of detected objects, YOLO can be employed to control robots [21]. In the proposed system, YOLOv5 [22] is employed to provide object position information to the robot arm controller.

YOLOv5 primarily consists of four models: YOLOv5x, YOLOv5l, YOLOv5m, and YOLOv5s. The YOLOv5x model is the most comprehensive, generally yielding the best results, while the other three models are simplified versions. The models differ in terms of feature extraction, convolutional kernels, specific network locations, parameter count, and overall size [23].

Given that the generated images contain only one part centrally positioned, an automatic labeler can be used. The "Automatic YOLO Labeler" library on GitHub [24] is capable of identifying the main object within a frame and saving its position. This library leverages the U^2-Net [25] for salient object detection, which removes backgrounds in images.

When the images are labeled, a background is added to the pictures and a filter to improve the training of the image recognition model. An illustration of the automatic labeling can be seen in Fig. 6.

D. The image recognition system

The automatic generation of the image recognition model can be divided into four main steps:

1) Generate images with different orientations.

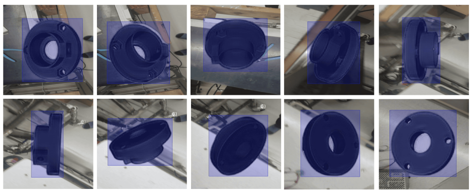

Fig. 4. The images are automatically labeled, and a new background is inserted.

2) Run the images through a cycle GAN to make the images look more realistic.
3) Then label the images, insert background images, and run the images through a filter.
4) Finally, the images are used to train the YOLOv5 model.

All of these steps can be executed automatically, and the image recognition model can be transferred to a robot arm and start picking objects automatically. An illustration of the steps can be seen in Fig. 5.

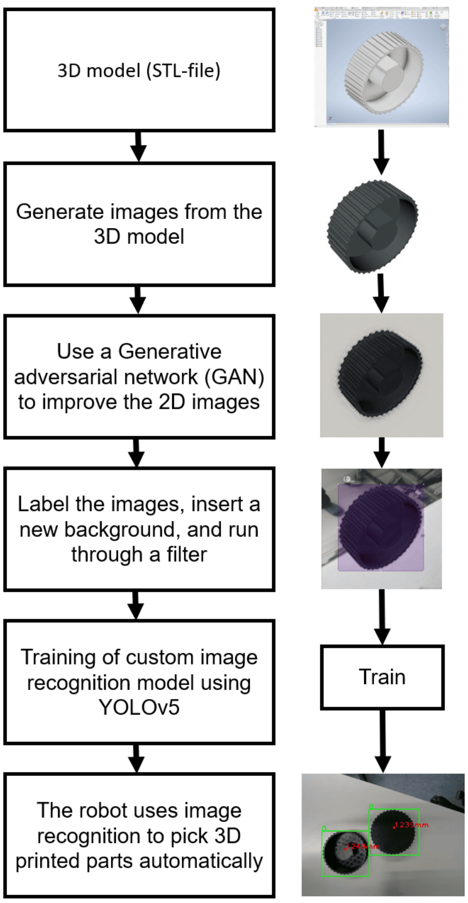

Fig. 5. On the left side, all the steps are used to create the image recognition model, and on the right side, the images are transformed.

III. System demonstration

A demonstration has been built to showcase how the system works. First, we explain how the image recognition model is created and then show video demonstrations of the system with robot arms.

A. Generating the image recognition model

The system is demonstrated using the three objects. A total of 12,000 images were generated by creating 4,000 images for each of the three 3D models with varying rotations. These images were then processed through the GAN to enhance realism and incorporate background images. As previously mentioned, the YOLOv5 algorithm is employed for the image recognition model, specifically using the largest pre-trained weights model, YOLOv5x [26].

Initial tests revealed that training the model with 100 epochs led to mislabeling and incorrect object identification, whereas training with 200 epochs resulted in overfitting, preventing the model from recognizing the objects. Consequently, training the model for 150 epochs yielded the best outcomes and the loss from the training can be seen in Fig 6. Additionally, an Intel RealSense D405 camera is utilized in the demonstration to obtain depth information from the camera frame.

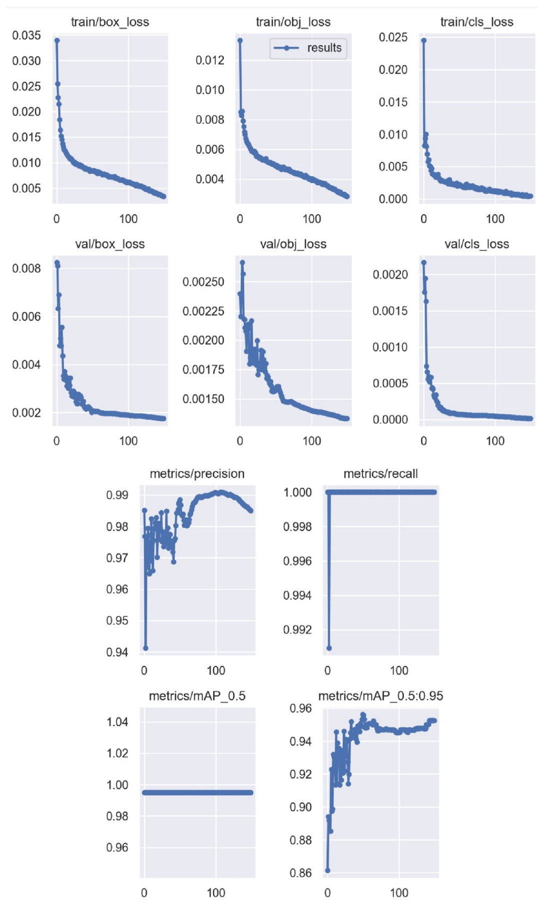

Fig. 6. The loss from training with 150 epochs.

B. Demonstrations 1 and 2

The initial two demonstrations illustrate the performance of the image recognition model in conjunction with different robot arm movements. In the first demonstration, the robot arm moves in a square pattern, increasing its height after each completed pattern. The image recognition model operates simultaneously with the robot arm's movement. A screenshot of this test is provided in Fig. 7, and the video can be viewed at https://youtu.be/6lGjiVP21Dg.

a)

b)

Fig. 7. Screenshot from the first demonstration, with a) depicting the camera approximately 160mm from the table and b) showing the camera 300mm from the table.

The second demonstration, available at https://youtu.be/6TmoyWvbd5Q, features the robot arm moving up and down slowly while the image recognition model runs concurrently.

Both demonstrations reveal that the image recognition model performs well at close distances. However, as the distance increases, the model's ability to recognize the object deteriorates.

C. Demonstration 3

The objective of the third demonstration is to automatically pick up an object using the image recognition model. A Nachi MZ07 six-axis industrial robot arm equipped with a suction gripper is utilized for this purpose, and the demonstration is limited to a single object. In this demonstration, the robot arm relies on the camera for navigation, adjusting its position based on the object's location within the camera frame. Once the suction cup is aligned with the object, the robot arm descends with a fixed movement to pick it up and then places it in a designated red box. To demonstrate the system's reliability, the robot arm repeats the process three times. The video can be found at https://youtu.be/oD82GAP8Ffs.

IV. Discussion

Traditionally, RMS needs to set up and program robots for each reconfiguration of the RMS. In this paper, we have proposed a method that can be used to automate the process of creating an image recognition model. This again can allow robot arms in manufacturing systems to become more automated and reduce the need for humans.

Moreover, in Industry 4.0, we have gotten new digital technologies such as digital twins, Big data, and simulation. These technologies can be used to digitalize manufacturing systems, but connecting or using these technologies with physical/real systems can be challenging. Using cycle GAN, can be an effective method to transform digital 3D models and make them look more realistic (real).

We also propose a system to generate the image recognition model automatically. The system takes in a 3D model, which is used to generate synthetic images. These images are then transformed with a cycle GAN, to make them more realistic. Then the images are automatically labeled, a background is added, and a filter is applied to make them ready to be trained. In this system, we use YOLOv5 since it is a fast method that can accurately detect objects but also tell where in the picture the object is. The image recognition model can be directly transferred to the robot arm for the pick and place of parts. It can also allow robot arms to work with objects without any human intervention.

The method achieved good results for close-ups, but several issues were experienced from a distance. To see what the image recognition model is focusing on, EigenCAM [27] is implemented. EigenCAM is a class activation map that can be used to find what pixels of the image the model is focusing on. After implementing EigenCAM, the main problem seems to be that the model is focused on specific parts of the part and not the general shape of the part. Another challenge is the effect of different lighting conditions and the background surface. If the light in the room is too strong or not strong enough can lead to no recognition. In addition, if the object is on a reflective surface and there is a lot of glare, the object will not be recognized.

Furthermore, as seen from the first two demonstration videos, the box is rarely recognized. However, the other objects are very well recognized at a close distance and the image recognition model can label them correctly. The box detection might be worse because it does not contain any clear feature that the image recognition model can focus on.

V. Conclusion and Further Work

In this paper, we have developed a method on how an image recognition model can be created automatically without the need for humans. The system takes a 3D model as input and generates images from the 3D model with different orientations. These images are transformed with a cycle GAN, to make them look more realistic. The Images can be automatically labeled, trained, and deployed on a robot arm for pick-and-place operations. This method can therefore be used to automatically create image recognition models, which can reduce the reconfiguration time of RMS.

We have also developed three demonstration videos. The first two videos show the performance of the image recognition model when the robot arm is moving. The third video shows pick and place with an industrial robot arm.

As mentioned in the discussion, there are many challenges with this system that must be solved before this system can be deployed in an RMS. For instance:

- To improve the detection of parts, the image recognition model must be improved. The first part is to find a method that allows for the detection of parts from a distance.
- In this paper, we create a cycle GAN that is used for 3D-printed parts in black. Further work should investigate if the same cycle GAN can be used from parts that come from CNC or turning machines. In addition, create a GAN which can work with all colors, not only black.
- The cycle GAN used in this system can be expanded and improved. This can be done by adding more images of real parts and using more 3D models. In addition, the system can be tested with other methods to create synthetic data, such as variational auto-encoders (VAE).

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References

[1] Yoram Koren and Moshe Shpitalni. "Design of reconfigurable manufacturing systems". In: *Journal of Manufacturing Systems* 29.4 (2010), pp. 130–141. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2011.01.001. URL: https://www.sciencedirect.com/science/article/pii/S0278612511000021.

[2] Yoram Koren, Xi Gu, and Weihong Guo. "Reconfigurable manufacturing systems: Principles, design, and future trends". In: *Frontiers of Mechanical Engineering* 13 (Nov. 2017). DOI: 10.1007/s11465-018-0483-0.

[3] Carin Rösiö and Jessica Bruch. "Exploring the design process of reconfigurable industrial production systems: Activities, challenges, and tactics". In: *Journal of Manufacturing Technology Management* 29.1 (Dec. 2017), pp. 85–103. DOI: 10.1108/JMTM-06-2016-0090.

[4] Halldor Arnarson et al. "Towards automatic configuration and programming of a manufacturing cell". In: *Journal of Manufacturing Systems* 64 (2022), pp. 225–235. ISSN: 0278-6125. DOI: https://doi.org/10.1016/j.jmsy.2022.06.005. URL: https://www.sciencedirect.com/science/article/pii/S0278612522001005.

[5] Ting Zheng et al. "The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review". In: *International Journal of Production Research* 59.6 (2021), pp. 1922–1954. DOI: 10.1080/00207543.2020.1824085.

[6] Ashutosh Singh, Piyush Gupta, and Mohammad Asjad. "Reconfigurable Manufacturing System (RMS): Accelerate Towards Industries 4.0". In: *SSRN Electronic Journal* (Jan. 2019). DOI: 10.2139/ssrn.3354485.

[7] Kai-Tai Song, Yu-Hsien Chang, and Jen-Hao Chen. "3D Vision for Object Grasp and Obstacle Avoidance of a Collaborative Robot". In: *2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*. 2019, pp. 254–258. DOI: 10.1109/AIM.2019.8868694.

[8] M. Fujita et al. "What are the important technologies for bin picking? Technology analysis of robots in competitions based on a set of performance metrics". In: *Advanced Robotics* 34.7-8 (2020), pp. 560–574. DOI: 10.1080/01691864.2019.1698463.

[9] Sergey Nikolenko. *Synthetic Data for Deep Learning*. Sept. 2019. DOI: https://doi.org/10.1007/978-3-030-75178-4.

[10] James Jordon et al. "Synthetic Data – what, why and how?" In: *arXiv* (May 2022). DOI: 10.48550/arXiv.2205.03257. eprint: 2205.03257.

[11] Alexandra L'Heureux et al. "Machine Learning With Big Data: Challenges and Approaches". In: *IEEE Access* PP (Apr. 2017), pp. 1–1. DOI: 10.1109/ACCESS.2017.2696365.

[12] Yanbiao Zou, Jiaxin Chen, and Xianzhong Wei. "A Calibration Optimization Method for a Welding Robot Laser Vision System Based on Generative Adversarial Network". In: *IEEE Transactions on Instrumentation and Measurement* 70 (2021), pp. 1–13. DOI: 10.1109/TIM.2021.3113950.

[13] Pradumn Mishra et al. "Footstep planning of humanoid robot in ROS environment using Generative Adversarial Networks (GANs) deep learning". In: *Robotics and Autonomous Systems* 158 (2022), p. 104269. ISSN: 0921-8890. DOI: https://doi.org/10.1016/j.robot.2022.104269. URL: https://www.sciencedirect.com/science/article/pii/S0921889022001580.

[14] Phillip Isola et al. "Image-to-Image Translation with Conditional Adversarial Networks". In: *arXiv* (Nov. 2016). DOI: 10.48550/arXiv.1611.07004. eprint: 1611.07004.

[15] Jun-Yan Zhu et al. *Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks*. 2017. DOI: 10.48550/ARXIV.1703.10593. URL: https://arxiv.org/abs/1703.10593.

[16] Kanishka Rao et al. "RL-CycleGAN: Reinforcement Learning Aware Simulation-to-Real". In: *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 2020, pp. 11154–11163. DOI: 10.1109/CVPR42600.2020.01117.

[17] Magnus Fredheim Hanssen. "Automatic Generation of Custom Image Recognition Models". UiT Norges arktiske universitet, May 2022. URL: https://munin.uit.no/handle/10037/25768.

[18] Karen Simonyan and Andrew Zisserman. "Very Deep Convolutional Networks for Large-Scale Image Recognition". In: *arXiv 1409.1556* (Sept. 2014).

[19] Aladdin Persson. *Machine-Learning-Collection*. [Online; accessed 8. Dec. 2022]. Dec. 2022. URL: https://github.com/aladdinpersson/Machine-Learning-Collection/tree/master/ML/Pytorch/GANs/CycleGAN.

[20] Joseph Redmon et al. "You Only Look Once: Unified, Real-Time Object Detection". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016, pp. 779–788. DOI: 10.1109/CVPR.2016.91.

[21] Hirohisa Kato et al. "Partial Depth Estimation with Single Image Using YOLO and CNN for Robot Arm Control". In: *2022 IEEE International Conference on Mechatronics and Automation (ICMA)*. 2022, pp. 1727–1731. DOI: 10.1109/ICMA54519.2022.9856055.

[22] ultralytics. *yolov5*. [Online; accessed 8. Dec. 2022]. Dec. 2022. URL: https://github.com/ultralytics/yolov5.

[23] Qisong Song et al. "Object Detection Method for Grasping Robot Based on Improved YOLOv5". In: *Micromachines* 12.11 (2021). ISSN: 2072-666X. DOI: 10.3390/mi12111273. URL: https://www.mdpi.com/2072-666X/12/11/1273.

[24] Abhi Panchal (abpanchal95). *yolo-labeler*. [Online; accessed 8. Dec. 2022]. Dec. 2022. URL: https://github.com/abpanchal95/yolo-labeler.

[25] Xuebin Qin et al. "U2-Net: Going deeper with nested U-structure for salient object detection". In: *Pattern Recognition* 106 (2020), p. 107404. ISSN: 0031-3203. DOI: https://doi.org/10.1016/j.patcog.2020.107404. URL: https://www.sciencedirect.com/science/article/pii/S0031320320302077.

[26] ultralytics. *yolov5*. [Online; accessed 14. Dec. 2022]. Dec. 2022. URL: https://github.com/ultralytics/yolov5/wiki/Train-Custom-Data.

[27] Mohammed Bany Muhammad and Mohammed Yeasin. "Eigen-CAM: Class Activation Map using Principal Components". In: *CoRR* abs/2008.00299 (2020). arXiv: 2008.00299. URL: https://arxiv.org/abs/2008.00299.

Paper 5

Reconfigurable Manufacturing: Towards an industrial Big Data approach

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Author's Contribution

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

Reconfigurable Manufacturing: Towards an industrial Big Data approach

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***Abstract*— As the world is moving towards more personalized and customized manufacturing, the manufacturing system needs to adapt. One method can be to integrate industry 4.0 concepts in reconfigurable manufacturing systems (RMS). This allows the manufacturing system to become more self-sustaining and flexible at the same time. There is however, a lack of research on how to integrate industry 4.0 concepts such as industrial Big Data (IBD) into RMS. This paper looks at how IBD techniques can be used on an RMS for classification and how to collect data from an RMS. A case study where five different movable platforms are identified with an accuracy of more than 85% is showcased.**

I. Introduction

With globalization, manufacturing companies are experiencing more fluctuations in product demand and unpredictable market changes [1]. At the same time, the manufacturing industry is moving towards more personalized production, which requires more frequent changes to the manufacturing system.

One approach to handle these changes is to have a reconfigurable manufacturing system (RMS). RMS is built on modularity and can rearrange itself based on functionality and production capacity. It provides a system that can quickly adapt to changes in the market at a reasonable cost.

RMS has the same high throughput as dedicated manufacturing lines (DML) and the agility of flexible manufacturing systems (FMS) while also being able to respond to changes in the market [2], [3]. It has been shown that taking DML and adding reconfigurability can give considerable capacity savings [4].

We are still in the early stages of research on RMS and how to implement RMS [5]. It has been found that there is a need for more research on reconfigurability towards industry 4.0 and how to use the industry 4.0 technologies in RMS [6].

Industry 4.0 brings new technologies such as simulation, autonomous robots, industrial internet of things (IIoT), cloud, cybersecurity, additive manufacturing, and Big Data (BD) and analytics [7]. These technologies enable manufacturing systems to be self-learning, controlling and aware. Industry 4.0 technologies are fundamental for the success of RMS [8], making the system more intelligent and self-sustaining.

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One concept from industry 4.0 that can allow an RMS to become smarter is BD and data analysis [8]. BD for an RMS can be used to store and gather historical data, trends and status of the system and machines [8].

BD can be used to manage large amounts of data in an efficient way [9]. The emergence of the internet has led to a large amount of data being collected that can not be handled with traditional tools for analysis and processing. Data collected from machines, the environment, humans and manufacturing processes can help improve the product quality and reduce production costs [10].

BD is a term often used to describe data that is challenging to manage with traditional tools [11]. It can be defined as, *"Big Data is the Information asset characterised by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value"* [12].

BD in industry 4.0 applications can be used for business intelligence, product quality enhancement, machine health prediction, production planning and fault tolerance [11]. Combining BD techniques with a cyber physical manufacturing system can allow for monitoring of the system and real-time decisions making for production scheduling [13]. It is also important to note that BD is not only related to the volume of the data but also the velocity, variety and veracity [14].

There are differences in how BD is used in different industries. For example Industrial Big Data (IBD) requires other processing techniques than for BD in social networks [15]. IBD is related to machine generated data instead of human related data and can be collected from machine controllers, manufacturing systems and sensors [16].

As mentioned before, RMS is built on modularity and can contain multiple platforms that are working together. In this paper we will define IBD for RMS, as data collected and analyzed from the whole manufacturing system. This includes multiple platforms, machines, sensors, logistics systems, ERP system and so on. Collecting and analyzing data from one platform or machine can be considered small data, but collecting and using data from multiple platforms and machines is IBD.

This paper will look at how IBD can be applied to an RMS and have the following contributions:

- We will look at how IBD can be collected from multiple platforms in an RMS.
- Look at how the data from a mobile robot that is part of an RMS can be used with IBD techniques and how the volume, velocity, variety, and veracity effects the

usability of the data.

The remainder of this paper can be structured as follows. Section II explains how the system is set up and it is connected. Section III goes through the four BD processing where the data is collected and how the data can be used to predict which platform is being moved. Discussion and conclusion in section IV and V.

II. Data processing

This section look at the system setup, how it is connected together.

A. System setup

An RMS often consists of different modules that can be assembled together based on a specific manufacturing task. For our experiments we have built a modular RMS of the following components:

- **Nachi platform:** A small anthropomorphic industrial robot
- **Scara platform:** A four joint SCARA robot
- **Conveyor lift:** A conveyor that can be moved up and down
- **Conveyor platform:** A normal conveyor to transport goods
- **3D print platform:** A creality CR-30 3D printer that can automatically print parts and move them out automatically.

These platforms can be moved and reassembled automatically with a mobile robot (MiR100). The mobile robot is equipped with a top module that has two pins that can move out to fasten itself to the platforms. It has a max payload of 100 kg but a towing capacity of 300 kg [17]. In this system, the platforms are being towed using the docking module.

A video on how the system works has been created and can be found `https://youtu.be/idA-TmYP45c`. The Video showcases the mobile robot picking up the five different platforms from various positions in the laboratory and assembling them to a manufacturing system. Afterward, the mobile robot takes the system apart and builds a new manufacturing system in front of the vertical storage lift (Compact lift).

B. Connection

This system consists of robots and other machines from different brands such as Nachi, MiR and Adept. These machines have different communication standards and it is time-consuming and tedious to create a separate method to collect data from each machine separately.

Another approach to collect data from the robots is to connect all machines to the Open Platform Communications Unified Architecture (OPC UA) server. The OPC UA is an IEC 62541 standard [18] and is widely accepted and used for industrial communications systems. It is seen as a reliable and secure standard for data exchange between components [19]. Connecting machines to the OPC UA server allows for a standardized method of communication and control.

The large conveyor, conveyor lift and 3D print platform use raspberry pi for control while the Scara and Nachi platforms have ubuntu machines. All these computers connect wirelessly to the OPC UA server, update data from the platforms to the OPC UA server and take data from the OPC UA server. This method allows for data collecting and monitoring while the system is running. Figure 1 shows how the system is connected with the OPC UA server.

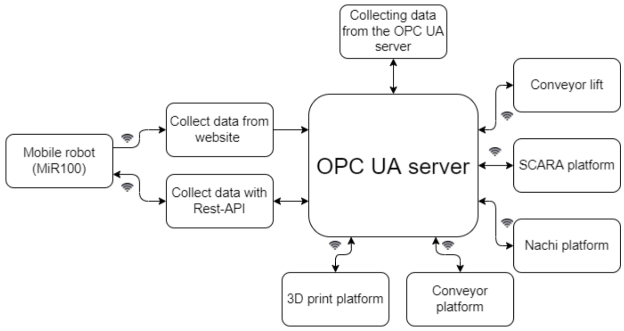

Fig. 1. The figure shows how all platforms and the mobile robot is connected to the OPC UA server.

C. Mobile robot connection

After all the platforms have been connected to the OPC UA server the mobile robot needs to be connected as well.

The mobile robot has a REST-API which can be used for simple control of the robot, gather information and changing settings on the robot. This interface uses JSON messages with get, post, and put messages. A python program is created, which works as a bridge between the OPC UA server and mobile robot. The program takes data from the mobile robot, sends it to the OPC UA server and takes control data from the OPC UA server, sends it to the mobile robot.

The REST-API gives somewhat limited information on the mobile robot and it is not possible to get data directly from the motors, power system, or sensors. If the payload is too heavy, the mobile robot will stop and give the operator the error message “motor stall detected!” or “power limit”. Thus, it can be beneficial to get data directly from motors, the power system, and various sensor data.

It is possible to get more data on the mobile robot by using a web browser and connecting to the IP address of the robot. Under “Monitoring” and then “Hardware health” you can get data on the internal Computer, Motors, Power system, Safety system, Sensors and Serial interface.

The data displayed in the browser is updated automatically every second. One method to collect this data is by using web scraping. Web scraping is a technique used to collect data from websites and save them to databases or files [20]. It can be used to extract data from websites automatically.

A second python program is created to collect the data from the web browser and put it in the OPC UA server. The program uses Selenium [21] which opens a chrome browser and goes to the IP address of the mobile robot. Then opens the “Hardware health” pages and extends all the windows to show the information from the mobile robot.

From the “Hardware health” page, there are 237 variables. For the sake of simplicity, saving time and processing power, only a set number of variables were chosen and limited to 84 variables. These variables are constantly read from the website and updated to the OPC UA server. The variables collected were on the motors, power system and sensors. A screenshot from the data in the OPC UA server can be seen in figure 2.

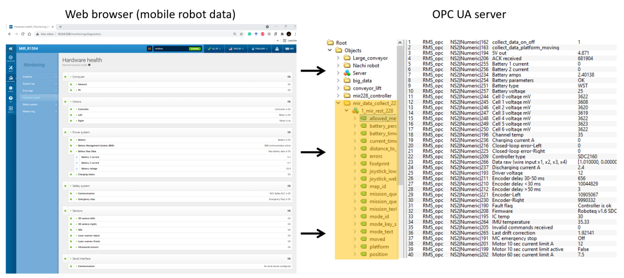

Fig. 2. The figure showcases the data taken from the web browser and transferred to the OPC UA server. The program UA Expert [22] is used to view OPC UA server, where the yellow square shows the data from the browser.

D. Data characteristics

When the data has been collected and processed it can be analyzed by looking at the characteristics. In the case of BD, it can be divided into four main characteristics volume, velocity, variety and veracity [14] [23]. Where:

- **Volume:** Is related to the amount of data/information being gathered. There is a need for algorithms that can handle and process large amounts of data in real time [14].
- **Velocity:** Is related to the speed at which the data is created, gathered and streamed [24].
- **Variety:** Data variety is related to the different data sources where the data is collected [24]. In industrial manufacturing systems, this often relates data from sensors, machines and other manufacturing equipment.
- **Veracity:** Is related to the quality accuracy and correctness of the data collected [25].

To evaluate the data from the mobile robot it can be beneficial to have the update rate and size of the data coming from the mobile robot. A simple python program is created, that measures how often the variable pitch from the gyroscope and the current of the left motor was updated. The data is updated every second. The data size collected was also measured, for all the 237 variables the size is around 2208 bytes.

When relating these four characteristics to the mobile robot:

- **Volume:** With the 237 variables, the data collected when the system is running is 2208 bytes per second. This can be considered as low volume and since this is data collection is from one module in an RMS, it will fall under small data instead of IBD. It should be noted that having multiple mobile robots or platforms would then create IBD.
- **Velocity:** The velocity of the data is rather slow (ones a second) and there is a chance of missing important readouts from the sensors. This can also affect the response rate from the sensors and it is more beneficial to have a higher update rate of the data.
- **Variety:** A total of 237 variables can be collected from the mobile robot on the internal Computer, Motors, Power system, Safety system, Sensors, and Serial interface. There is data on almost all components in the mobile robot. This data gives detailed insight into what the mobile robot is doing and the status of the mobile robot.
- **Veracity:** As mentioned, the data from the mobile robot isn’t made readily available by using their REST-API. There is no information on how the data is collected, transported, and the update rate of different data. It is hard to say something about the accuracy or correctness of the data, but a low update rate (velocity) can affect the data quality. With low velocity of the data the system can miss readouts from the sensors, which reduces the

III. Case Study

After setting up and connecting the system, the next step is collecting the data and using it to do classifications. This paper focuses on data collection for the mobile robot since it is used to reconfigure the system. The experiment is conducted in a controlled environment and only focuses on one platform. Thus, it will therefore fall under small data and not IBD. Regardless, we can still use the IBD techniques and see how the main characteristics of IBD can affect the data’s usability in making predictions.

A. Case study/idea behind the system

As mentioned before, the mobile robot is used to move the platforms around in the laboratory. All platforms in the system have a marker in front which the 3D cameras can detect and the marker allows the mobile robot to position itself accurately relative to the marker. However since all the platforms are on wheels, they can easily be tilted or moved out of position (e.g by a human operator). If a platform is moved by someone other than the mobile robot, the system will loose the position of the platform. Thus, there is a scenario where the mobile robot is driving around looking for platforms that have been moved out of its predicted position. Now the idea is to collect and use BD from the motors, power system and other sensors in the mobile robot in order to identify which platform is found. All platforms in the system vary in weight, size, wheel diameter etc. and requires an unique set of forces in order to be moved around.

In this paper six cases are considered, one for each of the five platforms and a sixth when there is no platform attached. The goal is to use data from the motors, battery and sensors with machine learning to classify what platform is being moved.

B. Big data processing

BD processing can be divided into four main steps; data collection, data preprocessing, data storage and data analysis [24].

- **Data collection:** Data can come from different sensors or other devices that are connected up to the internet. Therefore the first step is to collect the data from various sources.
- **Data storage:** The data that is collected needs to be stored. With BD, the data comes from different sources and is often diverse. It might need software that is compatible with multiple data types.
- **Data preprocessing:** Is used to clean and process the data that has already been collected. Some of the data that is collected might be invalid and needs to be removed. Other data needs to be unified and structured so that it can be analyzed with data from different sources.
- **Data analysis:** The last step is data analysis. Analyzing BD can give information and insight into processes that only BD analytics can give.

These four steps are used to process the data from the mobile robot.

C. Data collecting and storage

Machine learning can be used for various types of classification, but it needs historical data to train/fit a machine learning algorithm. In this case, data needs to be collected while the system is running.

To collect data, a program is created that drives the mobile robot to a random position and orientation in the laboratory. The area where the robot is driving is marked in figure 3.

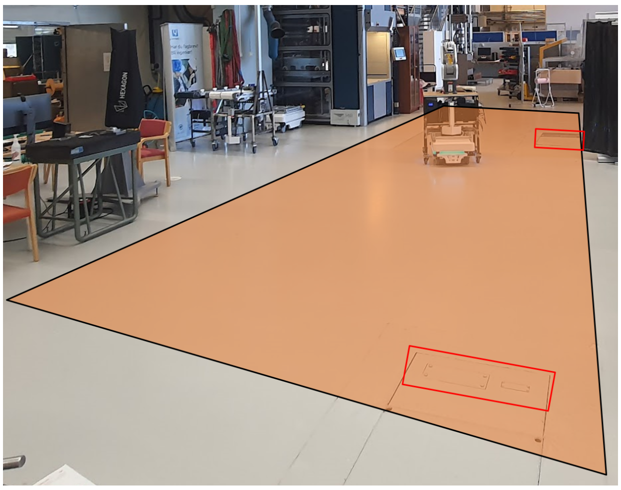

Fig. 3. Laboratory training arena: Collecting data for learning algoritm.

Data is collected while the mobile robot drives towards 30 random positions. When the mobile robot is done, the data is stored in a CSV file. The program is executed for all five platforms and then with no platform. The same data is collected a second time with 30 random positions. This data is used to validate and see if the classifier works.

A short video showcasing data collection from all platforms can be found at `https://youtu.be/0Sy457WWHbM`.

As can be seen in figure 3, two spots are marked with a red square. If the mobile robot drives over these areas, there is a high likelihood that the robot will get stuck because of the pumps. If it gets stuck, it will generate the error “Right motor stall detected!”, “Left motor stall detected!” or “Motor power usage above limit!”. When the mobile robot gets stuck, the data collection needs to be restarted.

An example from the variable “Battery 1 current” can be seen in figure 4.

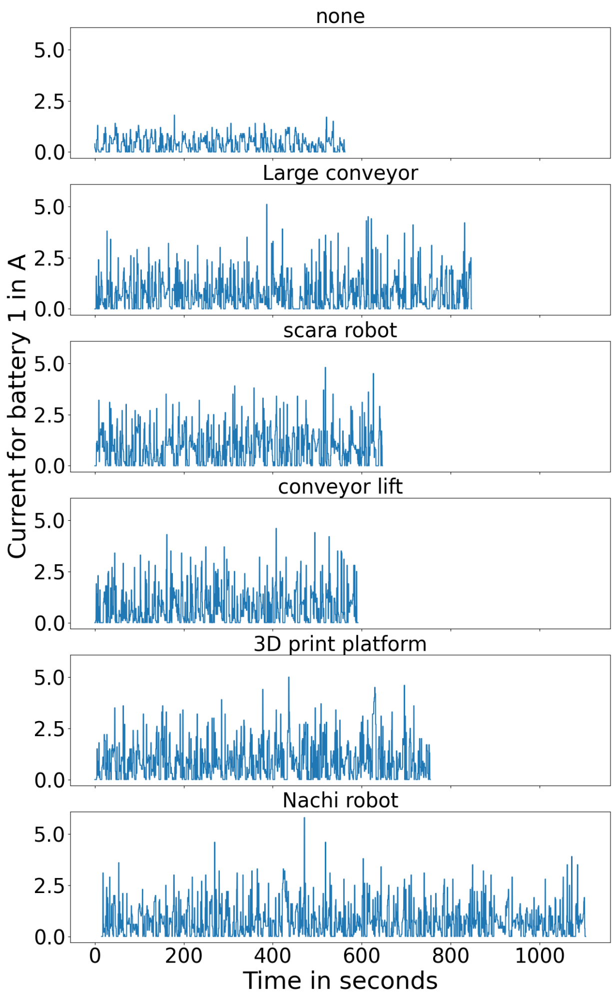

Fig. 4. The graph shows a example of data collected on for the variable “Battery 1 current”. It shows data from all five platforms and where there no platform (none).

From the figure 4, there is a clear difference when the mobile robot is not moving a platform and when it’s moving a platform. It can be harder to see clear differences between the platforms.

D. Data preprocessing and analysis

To train/fit the machine learning model the python library scikit-learn [26] is used. Scikit-learn is a well known machine learning library for python [27]. It has different machine learning algorithms for classification, such as naive Bayes classifier, k-nearest neighbors and linear support vector classification.

K-nearest neighbors is a simple and popular machine learning algorithm to do classification [28]. The algorithm can classify objects using the training data to find the nearest new object based on euclidean formula [29].

In this case, the k-nearest neighbor's method is used because of its simplicity and ease of use.

It is beneficial to have clear data, where it is possible to detect patterns. For instance, when the robot has arrived at its position, it stops and plans a new route before continuing. When the robot stops, the current of the motors and batteries becomes the same for all platforms. These measurements is removed to make the data more clear. After trimming the data, there are around 550 to 850 measurements from each of the 84 variables.

It is possible to get the current of the motors and the discharging rate of the battery. In addition, it is possible to get data on the current of both batteries and the channel temperature of the motor controller. These variables can be used to identify if the mobile robot is pulling heavy platforms.

Then from the 84 variables, six were used to train the classifier, as listed below:

- Battery 1 current
- Battery 2 current
- Discharging current A
- Motor current-Left
- Motor current-Right
- Channel temp (of motor controller)

After testing different combinations of the six variables, it was found that using the "Channel temp" and "Discharging current A" gave the best classification (80-85% accuracy). It is also possible to use the battery current or motor current, giving a little lower accuracy of around 80%.

IV. Discussion

In this paper, we have focused on collecting and analyzing data from the mobile robot in the RMS. Using IBD techniques on the mobile robot gives new opportunities to do classification with the sensors. As mentioned, the experiment with the mobile robot has small data and not IBD. However, the same methods and techniques from the experiment can be transferable to the other modules and data sources. In the literature, there is most focus on the amount of data in IBD cases. However, it is also important to consider the data's velocity, variety, and veracity.

The next step is to look at how all the data from the robot arms, conveyors, 3D printers and other data in the system can be used together. Merging data from different modules and sources in an RMS can allow the system to become more intelligent with the use of IBD.

Using the OPC UA server can be a good method to connect manufacturing equipment, allowing for simple data collection. However, it should be noted that connecting robots and other machines that don't support the OPC UA standard can be time-consuming work. For instance, the mobile robot has valuable data on its website, where a web browser is needed to collect the data. Creating programs for both web scraping and the REST-API for data collection is time consuming. It is more efficient if robot manufacturers make all sensor data available with an API or through the OPC UA server.

The data from the website is only updated every second and gives a low update rate. It can be easier to find patterns between variables if they are collected more frequently. This again makes it more challenging to use for machine learning, where you are trying to find differences between data. With a higher update rate, it can be possible to estimate how much payload the mobile robot is moving. By using the same sensors used to identify which platform is being moved.

In addition, having an update rate of once per second can impact the data quality. When relating this to the four V's, we can see that having a low velocity (update rate) can affect the veracity of the data.

V. Conclusion and further work

This paper looks at different applications of IBD for an RMS in Narvik. It focuses on the sensors data from the mobile robot and how this data can be used.

A classifier is created that uses sensor data from the mobile robot to identify which platform is being moved. Using the two variables "Channel temp" and "Discharging current A" gave the best result (80-85%) with the k-nearest neighbor's classifier. Other variables can also be used, such as the battery current and motor current, giving an accuracy of around 80%.

With the proposed system structure, a classifier can used to identify which platform is being moved.

In further work, we look at how to increase the accuracy of the classification. One method is to create a fixed path/routine for the mobile robot to drive. When the robot is driving the path/routine, data is collected, which can be used to classify which platform is being moved.

It should be noted that both classifiers can be improved by:

- Collected data over a longer period of time. More data usually means a more accurate classifier.
- More machine learning classification algorithms can be tested to improve the classifier.
- Other variables can be tested to improve the classifier.

References

[1] Y. Koren, X. Gu, and W. Guo, "Reconfigurable manufacturing systems: Principles, design, and future trends," *Frontiers of Mechanical Engineering*, vol. 13, 11 2017.

[2] Y. Koren, U. Heisel, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, and H. Van Brussel, "Reconfigurable manufacturing systems," *CIRP Annals*, vol. 48, no. 2, pp. 527–540, 1999. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0007850607632326

[3] Y. Koren and M. Shpitalni, "Design of reconfigurable manufacturing systems," *Journal of Manufacturing Systems*, vol. 29, no. 4, pp. 130–141, 2010. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0278612511000021

[4] A.-L. Andersen, T. Brunoe, and K. Nielsen, "Investigating the potential in reconfigurable manufacturing: A case-study from danish industry," 09 2015.

[5] R. Pansare, G. Yadav, and M. R. Nagare, "Reconfigurable manufacturing system: a systematic review, meta-analysis and future research directions," *Journal of Engineering, Design and Technology*, Aug 2021.

[6] M. Bortolini, F. G. Galizia, and C. Mora, "Reconfigurable manufacturing systems: Literature review and research trend," *Journal of Manufacturing Systems*, vol. 49, pp. 93–106, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0278612518303650

[7] L. Wang and G. Wang, "Big data in cyber-physical systems, digital manufacturing and industry 4.0," *International Journal of Engineering and Manufacturing*, vol. 6, pp. 1–8, 2016.

[8] A. Singh, P. Gupta, and M. Asjad, "Reconfigurable Manufacturing System (RMS): Accelerate Towards Industries 4.0," Feb 2019.

[9] K. Witkowski, "Internet of things, big data, industry 4.0 – innovative solutions in logistics and supply chains management," *Procedia Engineering*, vol. 182, pp. 763–769, 2017, 7th International Conference on Engineering, Project, and Production Management. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877705817313346

[10] J. Yan, Y. Meng, L. Lu, and L. Li, "Industrial big data in an industry 4.0 environment: Challenges, schemes, and applications for predictive maintenance," *IEEE Access*, vol. 5, pp. 23 484–23 491, 2017.

[11] M. Khan, X. Wu, X. Xu, and W. Dou, "Big data challenges and opportunities in the hype of industry 4.0," 05 2017.

[12] A. De Mauro, M. Greco, and M. Grimaldi, "A formal definition of big data based on its essential features," *Library Review*, vol. 65, pp. 122–135, 03 2016.

[13] Y. Koren, X. Gu, and W. Guo, "Reconfigurable manufacturing systems: Principles, design, and future trends," *Frontiers of Mechanical Engineering*, vol. 13, no. 2, pp. 121–136, Jun 2018. [Online]. Available: https://doi.org/10.1007/s11465-018-0483-0

[14] X. Zhang, X. Ming, and D. Yin, "Application of industrial big data for smart manufacturing in product service system based on system engineering using fuzzy dematel," *Journal of Cleaner Production*, vol. 265, p. 121863, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652620319107

[15] J. Yan, Y. Meng, L. Lu, and L. Li, "Industrial big data in an industry 4.0 environment: Challenges, schemes, and applications for predictive maintenance," *IEEE Access*, vol. 5, pp. 23 484–23 491, 2017.

[16] J. Lee, H.-A. Kao, and S. Yang, "Service innovation and smart analytics for industry 4.0 and big data environment," *Procedia CIRP*, vol. 16, pp. 3–8, 2014, product Services Systems and Value Creation. Proceedings of the 6th CIRP Conference on Industrial Product-Service Systems. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212827114000857

[17] M. I. Robots. Mir100. [Online]. Available: https://www.mobile-industrial-robots.com/en/solutions/robots/mir100/

[18] O. Foundation. Unified architecture. [Online]. Available: https://opcfoundation.org/about/opc-technologies/opc-ua/

[19] P. Drahoš, E. Kučera, O. Haffner, and I. Klimo, "Trends in industrial communication and opc ua," in *2018 Cybernetics Informatics (K I)*, 2018, pp. 1–5.

[20] B. Zhao, *Web Scraping*, 05 2017, pp. 1–3.

[21] "selenium," Sep 2021, [Online; accessed 23. Sep. 2021]. [Online]. Available: https://pypi.org/project/selenium

[22] "UaExpert "UA Reference Client" - Unified Automation," Sep 2021, [Online; accessed 24. Sep. 2021]. [Online]. Available: https://www.unified-automation.com/products/development-tools/uaexpert.html

[23] P. Zhang, F. Xiong, J. Gao, and J. Wang, "Data quality in big data processing: Issues, solutions and open problems," in *2017 IEEE SmartWorld, Ubiquitous Intelligence Computing, Advanced Trusted Computed, Scalable Computing Communications, Cloud Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, 2017, pp. 1–7.

[24] ——, "Data quality in big data processing: Issues, solutions and open problems," in *2017 IEEE SmartWorld, Ubiquitous Intelligence Computing, Advanced Trusted Computed, Scalable Computing Communications, Cloud Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, 2017, pp. 1–7.

[25] G. Bello-Orgaz, J. J. Jung, and D. Camacho, "Social big data: Recent achievements and new challenges," *Information Fusion*, vol. 28, pp. 45–59, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1566253515000780

[26] "scikit-learn: machine learning in Python — scikit-learn 0.24.2 documentation," Sep 2021, [Online; accessed 23. Sep. 2021]. [Online]. Available: https://scikit-learn.org/stable

[27] M. N. F. Hishamuddin, M. F. Hassan, D. C. Tran, and A. A. Mokhtar, "Improving classification accuracy of scikit-learn classifiers with discrete fuzzy interval values," in *2020 International Conference on Computational Intelligence (ICCI)*, 2020, pp. 163–166.

[28] R. Agrawal, "K-nearest neighbor for uncertain data," *International Journal of Computer Applications*, vol. 105, no. 11, 2014.

[29] Okfalisa, I. Gazalba, Mustakim, and N. G. I. Reza, "Comparative analysis of k-nearest neighbor and modified k-nearest neighbor algorithm for data classification," in *2017 2nd International conferences on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, 2017, pp. 294–298.

Paper 6

Investigation of wireless electrification for a reconfigurable manufacturing cell

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Author's Contribution

Hussein Mahdi designed and built the wireless charging component, while Halldor Arnarson was responsible for the RMS and battery platform.

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

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Technical paper

Investigation of wireless electrification for a reconfigurable manufacturing cell

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ABSTRACT

Reconfigurable manufacturing systems (RMS) with a rearrangeable structure can quickly adjust their productivity to meet the dynamic market changes and the demand for high-variety products. Industry 4.0 technologies have enhanced the RMS flexibility and made the automation of the reconfiguration of the manufacturing system possible. As an Industry 4.0 technology, wireless power transfer (WPT) can further increase the flexibility of RMS by providing safe, reliable, and maintenance-free autonomous charging. This paper examines the wireless electrification of RMS by investigating different WPT configurations that increase flexibility and autonomy, creating a highly flexible RMS. It also proposes a battery charging platform for further enhancement of the flexibility of RMS. As a low-cost WPT solution, the paper tests capacitive charging systems. The proposed charging system has about 135 W power transfer capability at a 5 cm distance and about 84% efficiency.

1. Introduction

Automated manufacturing systems have experienced noticeable changes passing through three main paradigms. The first paradigm is Dedicated Manufacturing System (DMS), which focuses on mass production for cost-effectiveness but with a low variation. The second paradigm is Flexible Manufacturing System (FMS) that address the production variety with low production volume. Finally, Reconfigurable Manufacturing System (RMS) is the third paradigm with high volume and high variation production combining the characteristics of the previous two paradigms. The RMS has a rearrangeable structure that can quickly adjust its productivity, variety, and flexibility based on the demand [1].

The dynamic market changes and the increasing competition between manufacturers to produce high-quality products with innovative technologies make the RMS an attractive paradigm. Bi et al. [2] proposed a systematic design methodology for RMS, including architecture, configuration, and control design. In practice, however, there is still a lack of research on how to solve design issues because a limited number of case studies are available [3]. Although the researchers have exerted considerable effort in developing RMS for several decades, there are still significant challenges, and barriers to the actual development of RMS in industry [4]. Rösiö et al. [5] explored the theoretical and practical challenges to achieving RMS design and summarized them in three main challenges: to use a structured design methodology and gain knowledge in reconfigurability and its characteristics, and to include the reconfigurability knowledge in a structured design methodology.

For research and educational purposes, the Engineering Research Center for Reconfigurable Manufacturing Systems at the University of Michigan developed a distributed reconfigurable factory testbed [6]. Kovalenko et al. [7] proposed real and virtual environment interaction (digital twin) framework to evaluate the performance of different machines and system configurations in a mixed virtual–real environment. Zuehlke D. [8] proposed adopting the basic principle of the Internet-of-Thing (IoT) in a testbed to proof-the-concept that moving toward intelligent manufacturing is a reality. Although the researcher tried to emulate RMS using a testbed, however, these systems require human intervention to rearrange the system, which is a time-consuming process and may suffer from limited positioning.

In general, the RMS suffers from several challenges, such as it is not the complete solution to meet all of the manufacturing requirements [2]. Besides, there is still no perfect or the most realistic model and method for RMS implementation. The rearrangement of the RMS structure is also time-consuming [6]. The RMS still depends on labor to rearrange the system structure and energize the platforms, which might affect the production time and limit the flexibility of the systems. And recently, the COVID-19 pandemic has added more challenges to

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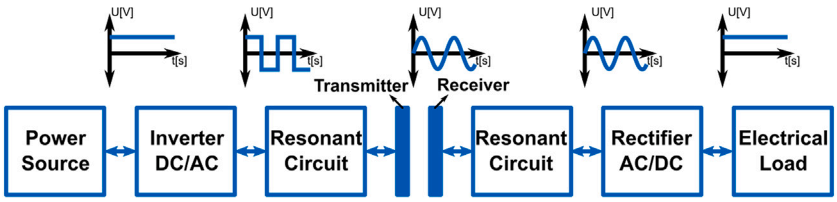

Fig. 1. An illustration of wireless electrification system.

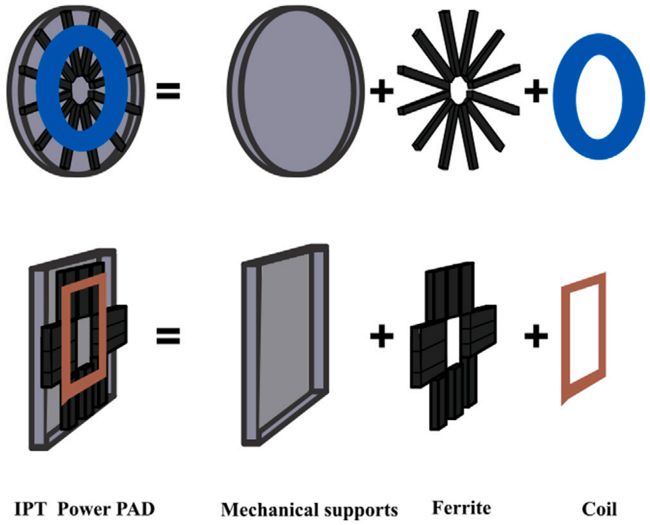

Fig. 2. An exploded view of IPT's different shape power pads.

the manufacturing systems, including lockdown and maintaining social distance [9], which can increase the rearrangement time of RMS and reduce its flexibility.

To tackle the challenges above, Arnarson et al. [10] introduced the autonomous RMS by using a mobile robot to rearrange robot arm platforms automatically to achieve flexibility and mobility. As an expansion, Arnarson et al. [11] presented a highly flexible RMS by retrofitting a number of manufacturing machines to automate the reconfiguration of the system, decrease the setup and programming time, and enhance the system's flexibility. Randanovi et al. [12] tried to solve one of the common problems of the conventional wired electrification of RMS by standardizing the connectors and plugs. In contrast, Arnarson et al. [11] considered Wireless Power Transfer (WPT) as an emerging industry 4.0 technology for electrifying RMS that tried to remove the plugs, connectors, and cables to increase the flexibility and reliability of the electrification of RMS.

The previous research on RMS investigated testbed manufacturing cells which are aimed for educational and research purposes [6–8]. Recently, researchers tried to develop a practical RMS using industry 4.0 technologies [11]. However, the proposed system still requires labor to connect the machines to electricity or charging batteries. As an industry 4.0 technology, wireless electrification can provide the required energy to these platforms without mechanical contact, similar to how IoT communication brings wireless communication. Previous research investigated wireless electrification for various applications in general and industrial robots in specific. There are also various products for robot charging applications on the market. However, the focus is more on one type of WPT, which utilizes magnetic fields.

This paper investigates the state-of-the-art WPT for robotics in manufacturing applications in the literature and on the markets. Based on the investigation, the paper proposes a novel approach to the electrification of manufacturing applications based on Capacitive Power Transfer (CPT), which creates a new foundation for RMS that significantly increases the system's flexibility and reconfigurability. Thus, we propose and test a battery platform using CPT that utilizes electric fields to wirelessly electrify other manufacturing machines in an RMS. We can summarize the main contribution of the paper as follows:

Table 1
A comparison between the main three groups of WPT.

	Near-field	Mid-range	Far-field
Wave	Electric/Magnetic	Magnetic	Electromagnetic
Rang	Very short (cm)	short (m)	Medium long (km)
Frequency	low high	high	Very high extreme high
Power	low moderate	Moderate	Very low
Architecture	Simple/Moderate	Complex	Complex

- Investigating wireless electrification for manufacturing applications.
- Proposing an autonomous battery platform based on CPT for electrification of RMS.
- Build an RMS and demonstrate how it can be energized using wireless power transfer to increase flexibility and automation.
- Simulating, testing, and demonstrating the CPT system with the battery platform to prove the concept.

We organize the rest of this paper as follows: Section 2 presents the general concept of wireless electrification of RMS. Section 3 investigates the state-of-the-art WPT for robotics and manufacturing applications. Section 4 expands the RMS by building a battery platform that can power the system in static, dynamic, or quasi-dynamic mode. Section 5 presents the experimental and testing results of the CPT system. Section 6 gives a comprehensive discussion of WPT systems in general and CPT systems in specific. Section 7 concludes this work and presents our future works.

2. Wireless electrification

Wireless electrification, or WPT, is to transfer electric power without mechanical contact. International Telecommunication Union [13] defines WPT as "*the transmission of power from a power source to an electrical load using the electromagnetic field.*" The three main groups of these technologies are near-field, mid-range, and far-field [14]. The classification depends on the size of the transmitter and the receiver, and the transfer distance. Table 1 summarizes a comparison between the three main groups in terms of the type of wave, distance range, operating frequency range, power level, and system architecture.

Near-field WPT utilizes medium- to high-frequency range electromagnetic fields for high-power charging applications. Thus, the separation distance between the transmitter and the receiver is in the cm range. WPT can provide static, quasi-dynamic, and dynamic electrification [15,16]. It can also energize the system autonomously and potentially address the challenges in the conventional conductive charging approach, including long charging time, wear and tear of the contractors and plugs, and the hazard of the electric shock. Using WPT in RMS provides autonomous electrification and removes the time consumption of plugging the cables.

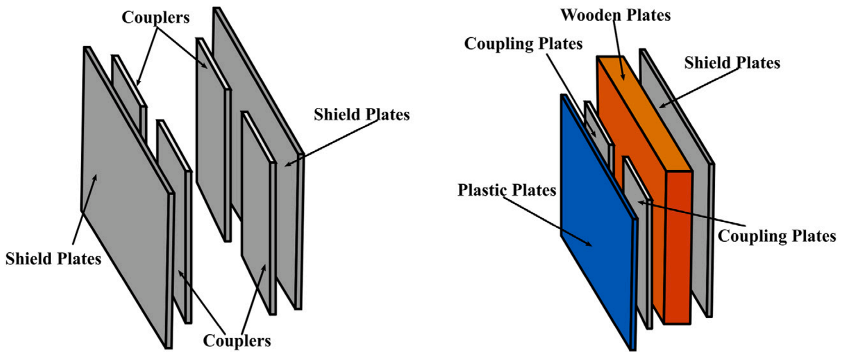

Fig. 3. Capacitive coupler: six plates CPT system (left) and an exploded view of capacitive couplers (right).

Fig. 1 illustrates the functional blocks in the WPT system. The inverter converts the DC source voltage into a square wave which depends on the operation frequency of the inverter. The resonant circuit improves the system's overall efficiency by minimizing the reactive power, achieving soft-switching, and high misalignment tolerance. The resonant circuits also act as low-pass filters that filter out the high harmonics in the current of the inverter and reduce electromagnetic interference. Finally, the rectifier stage converts the ac resonant current into a DC. The wireless electrification system might need other DC/DC converters, for instance, between the power source and the inverter or between the rectifier and the load, which depends on the design specifications. The near-field WPT embraces three sub-group, namely, Inductive Power Transfer (IPT) and Capacitive Power Transfer (CPT).

2.1. Inductive power transfer

Inductive electrification, or IPT, operates on loosely coupled magnetic fields between transmitter and receiver coils. It includes inductive and inductive resonance. The only difference between inductive and inductive resonance is the resonance compensation circuits. The transmitter and receiver of the IPT system are also called "power pads," composed of coils to produce alternating magnetic fields, Ferrite to align and shield the fields, and mechanical supports, as shown in Fig. 2. The Litz wire provides a solution for increasing the conductivity of the coil at high operation frequency while screening the magnetic fields. Nevertheless, both the Litz wire and the Ferrite make the pads expensive, heavy, and fragile [17]. Depending on the dimension of the power pads, the coupling and hence the efficiency of IPT systems can significantly change with the separation distance, and misalignment changes [18]. Increasing the power pads is one way to achieve better misalignment performance [19]. However, it will increase the overall system's weight, cost, and design complexity.

2.2. Capacitive power transfer

Capacitive electrification, or CPT, utilizes alternating electrical fields that are confined between transmitter and receiver plates, also called "capacitive couplers," to transfer power. We can build CPT systems using two-, four-, or six-plates configurations. Fig. 3 illustrates a six-plate configuration of the CPT system's transmitter–receiver, which includes four plates forming the capacitive couplers and two plates screening the electric fields. The six plates configuration can reduce the safety clearance range from 1 m to 10 cm [20]. The transmitter and the receiver consist of aluminum capacitive couplers, plastic plates, wooden plates, and shielding plates. The plastic plates offer insulation protection, while the outer plates work as a shield to screen the leakage electric fields and offer extra protection. The wooden plates insulate the screening plates from the couplers. Based on the structure, the capacitive coupler is lighter and costs less than the IPT power pad. The CPT system is still sensitive to misalignment [20], yet it has a much better misalignment performance than the IPT system [17].

Table 2
A Comparison between IPT and CPT.

	IPT	CPT
Power Range	tens of kW	hundreds of W
Eddy Current Losses	high	low
Misalignment Performance	bad	good
Cost	high	low
Pads'/Couplers' Weight	heavy	light
Efficiency	high	medium
Fields Shielding	complex	simple

To sum up, IPT systems contain Litz wires and magnetic screenings, which are expensive, fragile, and heavy. Besides, the magnetic fields can interact with the metal parts of the platforms resulting in high eddy losses, which can increase the temperature of the platforms. As an alternative, CPT is more suitable for the platform as it tackles the challenges that face IPT systems. Table 2 lists a comparison between IPT and CPT systems in terms of power density, losses, misalignment performance, cost, weight, and efficiency.

3. The state-of-the-art WPT for robotics in manufacturing applications

Wireless power transfer has several distinctive advantages, including reliability, flexibility, and autonomy, making it an attractive solution in many applications. More than 30 years ago, Esser and Skudelny [21] investigated wireless inductive electrification using rotatable transformers fixed on the joint of a robot. They managed to transfer 20 kW over 100 μm. About ten years later, Hirai et al. [22] proposed IPT for an autonomous decentralized manufacturing system for electrification and data transfer purposes. The proposed system transferred a consecutive 1250 GB data transmission under the continuous 2 kW power transmission over 100 μm to 500 μm to a servomotor. Since then, the research has focused more on IPT industrial robot applications. In this section, however, we focus on the most recent studies on high-power WPT for robotics in manufacturing applications and investigate the available WPT solutions on the market. Low power and data transfer are out of the scope of this paper.

3.1. Robotic arms

Wireless power transfer offers robotic arms distinct merits such as no risk of electrocution, high convenience and robustness, and water- and dust-proof [23]. Thus, wireless electrification (WPT) applications for robot arms have gained more attention. Inductive electrification (IPT) is the common approach used in robotic arms by applying magnetic connections at the joint. Han et al. [23] energized two permanent magnet dc motors in a robot arm using IPT. And they reported output power of 142.9 W at 88.7% transmission efficiency. Besides, Kikuchi et al. [24] proposed IPT to power a robot manipulator used

Table 3
Summary of WPT applications in the literature.

Ref.	Application	Power [W]	Eff. [%]	Freq. [kHz]	Dist. [mm]
[23]	Robotic Arm	142.9	88.7	85	100
[24]	Robotic Arm	311.6	92	246	5
[25]	Robotic Arm	39.9	78	6780	250
[26]	Robotic Arm	85.9	84	150	100
[28]	Logistic Robot	150	90	300	200
[30]	Transport Robot	30	74.2	100	8

in warehouse automation systems. They built a prototype with a maximum power of 311.6 W and total efficiency of 94%. Moreover, Tokano et al. [25] experimented with a 39.9 W and 78.0% power-delivery efficiency for conventional robot arms. Finally, Wu et al. [26] proposed and tested a 85.9 W multidegree freedom and bidirectional transmission capability WPT system for robot arm's joints (see Table 3).

3.2. Transport and mobile robots

For flexible manufacturing, IPT systems have found their application with clean factory automation through the dynamic powering of vehicles on monorails which have spread to floor-mounted automatic guided vehicles and other industrial vehicles [27]. Zhang et al. [28] proposed an IPT system for a logistic robot within a confined three-dimensional space around the charging station. In addition, Lee et al. [29] proposed an IPT system for continuous wireless powering of multiple transport robots in an electrified monorail system. Table 3 lists the available wireless solution in the literature.

3.3. WPT on the market

Many manufacturers are working to develop WPT technologies for robot joints of robotic arms applications. TDK [31] offers a 200 W IPT system for mobile robots that has a power distance 100 mm to 300 mm, 88% efficiency, and a 50 W IPT system for robot arms. Moreover, Waypoint Robotics [32] offers a 300 W non-contact charging and energy delivery system that ensures maximum availability of their mobile robot fleet. Delta [33] provides a 1 kW IPT system for mobile with a maximum efficiency of 93%. In addition, Wibotic [34] provides a 300 W IPT charging solution for mobile robots. Table 3 lists the WPT systems on the market for manufacturing.

Thus far, the previous research has focused more on IPT industrial robot applications and less focus on manufacturing cells. The examples in the literature and on the market only use IPT. The IPT systems comprise expensive, fragile, and heavy components, and they have high eddy losses. In contrast, CPT is more suitable for the platform as it tackles the challenges that face IPT systems. To the authors' knowledge, there has not been any investigation on CPT to power a manufacturing cell. In the next section, we propose a CPT system for the electrification of a RMS manufacturing cell.

4. RMS with battery platform

4.1. The structure of the proposed RMS

Previously, Arnarson et al. [11] proposed an RMS consisting of five platforms; two industrial robots (Scara and Nachi), a conveyor platform, a conveyor lift platform, and a 3D printing platform. The RMS can move and rearrange automatically with the help of a mobile robot in a manufacturing environment that is flexible and scalable, and it has the potential to be fully autonomous. A demonstration video [35] shows the mobile robot picking up the platforms and assembling two manufacturing layouts. In this paper, we expand the system by proposing a battery platform to increase the flexibility of the RMS (see Fig. 4).

Table 4
Power usages of the modules.

Module	Power [W]
IRB1 (Scara)	141
IRB2 (Nachi)	242
Conveyor	38
Conveyor lift	54
3D printer	350

4.2. Battery platform

In this paper, we suggest adding two extra platforms to the system, containing only batteries. While one platform is charging, the other is powering the system, as shown in Fig. 5. When the platform powering the system is running out of power, a fully-charged battery platform can replace it. The capacity of the batteries on the battery platform decides how long the platform can power the system. The mobile robot drives to pick up a full battery platform at the charging station and places it within the RMS. Then, the mobile robot picks up the empty battery platform and transports it to the charging station. Afterward, the mobile robot can do other logistics tasks. A video https://youtu.be/o3jhAhYdPUc demonstrates a simulation of how the battery platforms change.

The battery platform can also power other platforms in the system in the static, dynamic, or quasi-dynamic modes, as shown in Fig. 6. Thus, the mobility of the battery platform gives the system more flexibility, reconfigurability, and reliability. In addition, the battery platform can also charge the mobile robot. When the mobile robot is moving the battery platform, the battery platform can charge the mobile robot. This allows a flexible method to charge the mobile robot without the need to turn to a charging point, but it depends on the capacity of the batteries.

5. Experimental validation and testing

5.1. The power requirement

All the platforms have small computers and microcontrollers to collect data from the sensors and operate independently. For each platform, we measured the power consumption under normal operation. This means measuring the total power consumption of the computers and robots/conveyors while they are moving. Table 4 lists the power usage of all platforms under test operation conditions. The platforms require low power consumption to run the system, which ranges 43 W to 350 W. As the required power is not high, using WPT can be a flexible solution to power the system.

It should be noted that the conveyor uses only 38 W in this system since the motor uses a gearbox with a 75:1 ratio. The idea of this demonstration is to show that a manufacturing system that has low power consumption can be wirelessly powered. Each platform is equipped with batteries that can be used to supply the manufacturing platforms with power peaks as long as the power draw is not higher than from the WPT system. Large machines, such as CNC and 3D printers, consume large power, which will be a challenge to electrification wirelessly. These large machines are not reconfigurable, as they require re-calibration; hence the reconfigurable platforms are rearranged around them. Thus, we will not consider wireless electrification for these large machines.

5.2. Capacitive wireless electrification for RMS

As an inexpensive and simple solution for electrifying the RMS, we will continue investigating the CPT system. We use the same configuration shown in Fig. 3 to build the capacitive couplers. The size of the couplers is 25 × 25 cm, the wooden plate is 30 × 70 cm, and the shield plate is 25 × 70 cm. The distance between the plates on

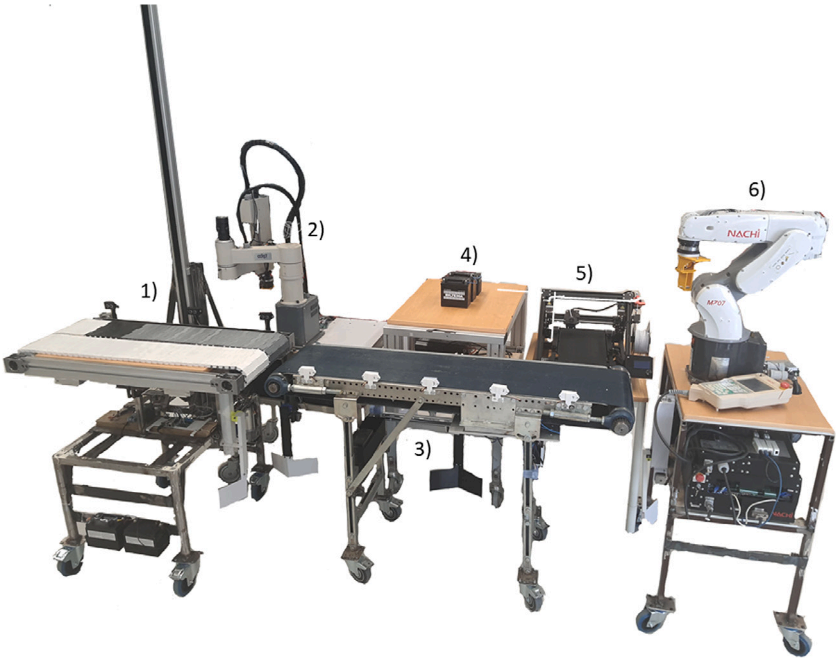

Fig. 4. The expansion of RMS with battery platform. (1) conveyor with lifting (2) Scara platform, (3) conveyor, (4) battery platform, (5) 3D printer, and (6) Nachi platform.

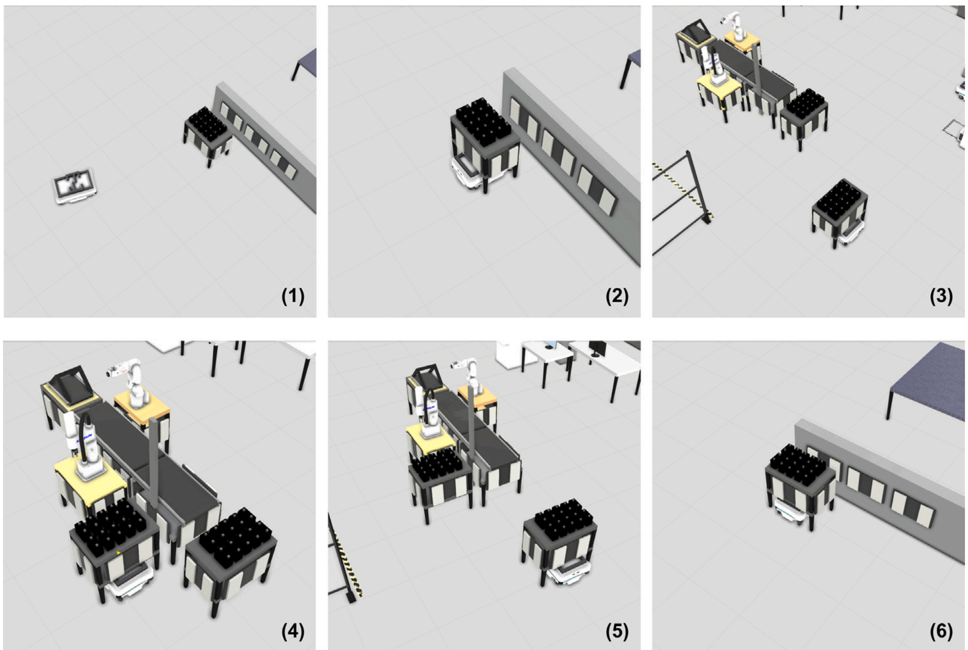

Fig. 5. The operation principle of the battery platform: The mobile robot drives to pick up a full battery platform (steps 1 to 4), picks up the empty battery platform, and transports it to the charging station (steps 5 to 6).

the same sides is 10 cm. We utilize a GaN bridge inverter (Infineon EVAL1EDFG1HBGAN [36]) and four Schottky diodes (C6D04065 A [37]) to build the rectifier bridge. We also used air-cored inductors in the series resonant circuit to compensate both transmitter and the receiver sides with the inductance of 235.1 μH for L_T and 268.3 μH for L_R.

Fig. 7 presents testing results in the laboratory. The CPT output power is about 109 W with an efficiency of about 73% at 150 V input voltage and 1.3 MHz. The maximum voltage is more than 600 V across the couplers, and the maximum current through the receiver side inductor is about 1 A. Due to the harmonics, the current is not a pure sine waveform. This video https://youtu.be/-mubROmWRcI shows the testing of the CPT system.

We can further increase the output power by increasing the input voltage. To further improve the efficiency and increase the transmitting distance, we also increased the size of the coupling plates to 30 × 45 cm, and the distance between the couplers was 18 cm. The CPT output power is about 134.6 W with a total efficiency of about 84% at 1 MHz and about 5 cm distance between the transmitter and the receiver.

Fig. 8 shows the separation distance's effect on the CPT system's efficiency. The efficiency decreases with the increase of the distance, which we can attribute to the sensitivity of the compensation circuits (i.e., the resonant frequency) to the distance change. One way to

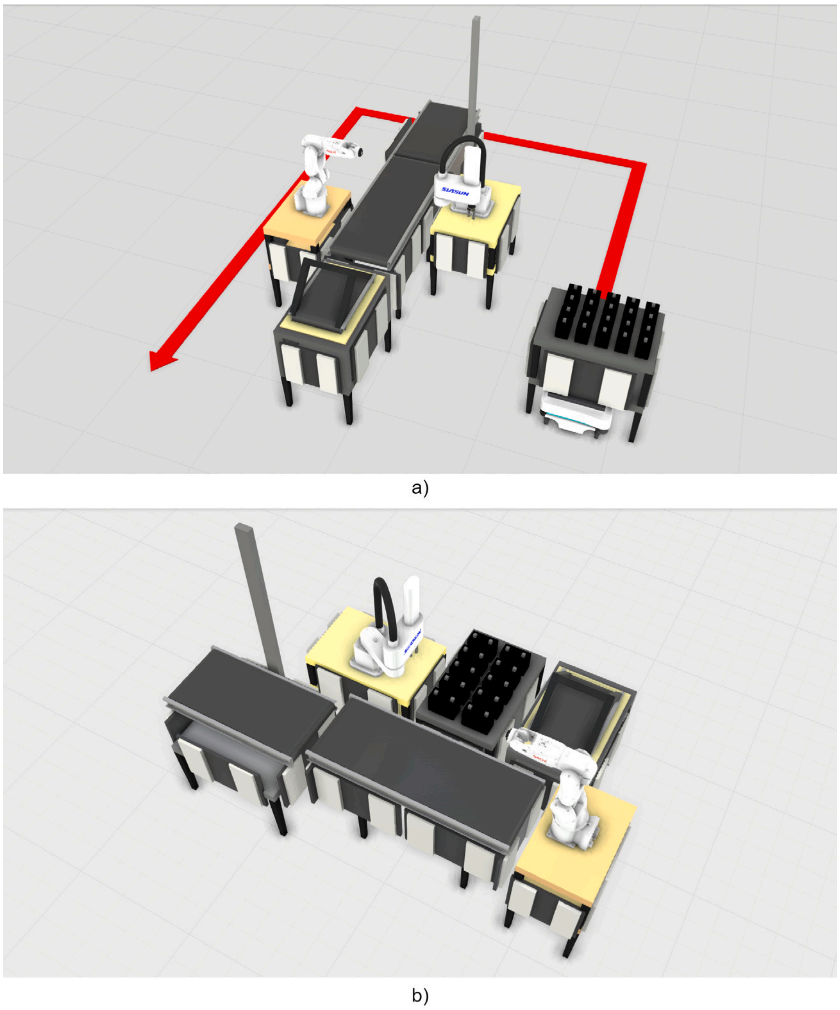

Fig. 6. The two operation modes of battery platform: (a) The dynamic mode. (b) the static mode.

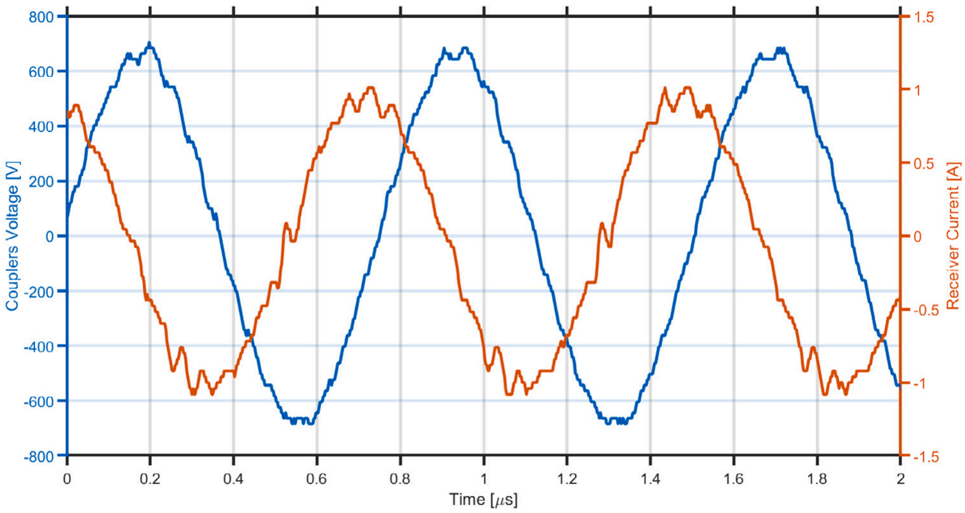

Fig. 7. The voltage across the couplers and the current on the receiver side.

enhance the efficiency is by proposing control techniques to operate the inverter at a frequency that can adapt to the change in the distance.

When the maximum output voltage of the inverter is 300 V, the voltage across the couplers can reach about 1.9 kV, which is high voltage stress, as shown in Fig. 9. Fig. 10 shows the currents through the transmitter's and the receiver's indicators. The transmitter's current is about 2.2 times the amplitude higher than the receiver's current.

To prove the concept, we designed a battery platform with three batteries connected in parallel as a power source and the CPT system transmitter plates, shown in Fig. Fig. 4. We also equipped it with

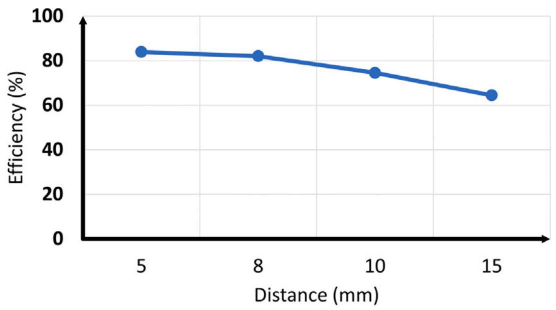

Fig. 8. The efficiency of the CPT system versus the change in the separation distance between the platforms.

a converter that steps up the 12 V input voltage to 300 V voltage to achieve the required electric field strength. Moreover, we retrofitted the conveyor platform with the receiver couplers, and the step-down converter stage converted the output voltage from 300 V to 12 V. The functional blocks of the proposed CPT system show the parts of the systems and the components that are used in each part, as shown in Fig. 11.

Fig. 12 shows the demonstration of a CPT system between two platforms. In the demonstration, the mobile robot picks up the battery platform and brings it to the other platforms. Then, the battery platform starts energizing the conveyor platform, which is not equipped with batteries. Fig. 12 and the video https://youtu.be/KRwIdJ8fu5A show the experiment described above.

6. Discussion

Arnarson et al. [11] tried to tackle the challenges that RMS encounters by retrofitting manufacturing machines with industry 4.0 technologies. Their system can automatically arrange five platforms using a mobile robot for manufacturing a specific product. The system is flexible and scalable and can be autonomous, but all platforms are energized with batteries, which require human intervention to charge them. Thus, there is a need for an autonomous method for charging or electrifying the platforms to make the proposed system fully autonomous.

Dealing with the charging problem, Randanovi et al. [12] tried to solve one of the common problems of the conventional wired electrification of RMS by standardizing the connectors and plugs. Another solution is to use the same principle of charging a mobile robot through electro-mechanical parts, but this solution limits the platforms' positioning and increases the need for maintenance due to the wear and tear of these contacts.

From the opposing point of view, Arnarson et al. [11] proposed WPT, which tried to remove the plugs, connectors, and cables to increase the flexibility and reliability of the electrification of RMS. They also proposed WPT as industry 4.0 technology to increase the flexibility of the manufacturing system. One of the industry 4.0 technologies is the IoT, where we can communicate wireless between machines and sensors. Similarly, we can wirelessly electrify machines and other robots, removing restrictions and making them more flexible. It was, therefore, suitable to include WPT as an industry 4.0 technology and be implemented in the following paradigms of RMS.

Using WPT, we can utilize static or dynamic WPT to electrify the system to improve its flexibility and reduce the time to reconfigure the system [11]. The dynamic WPT can electrify the platforms and the mobile robot, increasing the system's extent and cost. In contrast, static WPT offers a good option to electrify the platforms from each other or a main fixed machine. The system will get better efficiency by correcting the misalignment between the platforms.

The researchers previously investigated WPT for industrial robot electrification with power ranges from tens to hundreds of watts. On the market, there are already commercial solutions with power ranges 50 W to 300 W. However, IPT is commonly used in the literature and industrial robot applications markets. We can utilize static IPT for high power requirements of the platforms or vast distances between them. However, IPT systems contain heavy, fragile, and expensive power pads and are sensitive to misalignment and eddy losses, decreasing the overall system efficiency.

One limitation of the WPT system which proposed to RMS in [11] is that when the platforms are not connected to a wireless charging point, they need to be moved back when their battery is running low. As a novel approach to the electrification of manufacturing applications, we proposed a battery platform that can electrify other platforms of mobile robots in static, dynamic, or quasi-dynamic charging modes to increase the flexibility and reliability of the WPT charging system.

Building this platform, we increased the distance between the couplers to 5 cm and the input voltage to 300 V to achieve 134.6 W and about 84% system efficiency at 1 MHz. The proposed system demonstrated that static CPT is a low-cost alternative. However, the system's efficiency can be degraded with the increase in the distance as the system operates in an open loop. To solve this problem, we will prove a control technique that changes the operating frequency with the change in the separation distance to track the maximum efficiency of the system.

The results also showed that increasing the input voltage increases the voltage across the couplers to about 2 kV, which increases the electric fields between the plates. However, the shielding plates screen the electric fields from interacting with the platform's parts or endangering the workers near the plates. The results also show that the current on the transmitter and receiver sides have harmonics, which can have electromagnetic interference with the system. We can tackle this problem by investigating better compensation circuits to filter out the harmonics and enhance the electromagnetic compatibility of the CPT system in RMS.

Implementing the battery platform allows us to reconfigure the system in any place. Depending on the capacity of the batteries, the battery platform can charge other platforms or mobile robots in static or motion, which can further increase the flexibility and reliability of the system. For instance, the battery platform can electrify the 3D printer platform, which has the maximum power usage of 350 W, for 8 h if we connect ten batteries in parallel. The capacity of the batteries is an essential factor that decides the charging period, but increasing the capacity by adding more batteries will increase the weight of the platform resulting in a docking problem for the mobile robot, as Arnarson et al. [11] discussed.

7. Conclusion and future works

This paper investigated WPT solutions for robotics in manufacturing applications. Focuses are more on IPT industrial robot applications manufacturing cells in the literature and on the market. However, the paper presented the general concept of wireless electrification using near-field WPT technologies, namely, IPT or CPT for RMS. It also proposed and tested a static CPT system as an inexpensive and light alternative for manufacturing cells, as the proposed system comprises no expensive, fragile, or heavy parts. Utilizing a six-plates configuration, the safety clearance of the CPT system can be reduced to a few centimeters. As a novel approach to the electrification of manufacturing applications, a battery platform is designed based on the CPT system, which is a part of an RMS consisting of five other platforms: two industrial robots (Scara and Nachi), a conveyor platform, a conveyor lift platform, and a 3D printing platform. The battery platform can charge the batteries of other platforms. Hence it gives the system more flexibility, reconfigurability, and reliability. The proposed CPT system gives an output power of 135 W with 84% efficiency at 5 cm separation

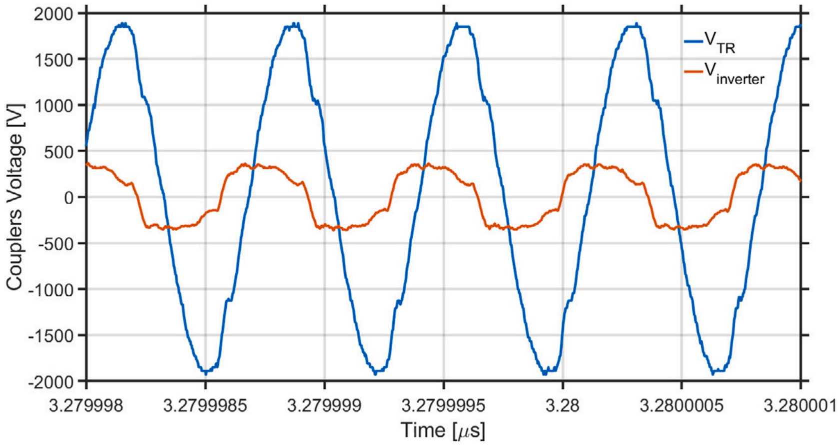

Fig. 9. The output voltage of the inverter ($V_{inverter}$) and the voltage across the couplers (V_{TR}).

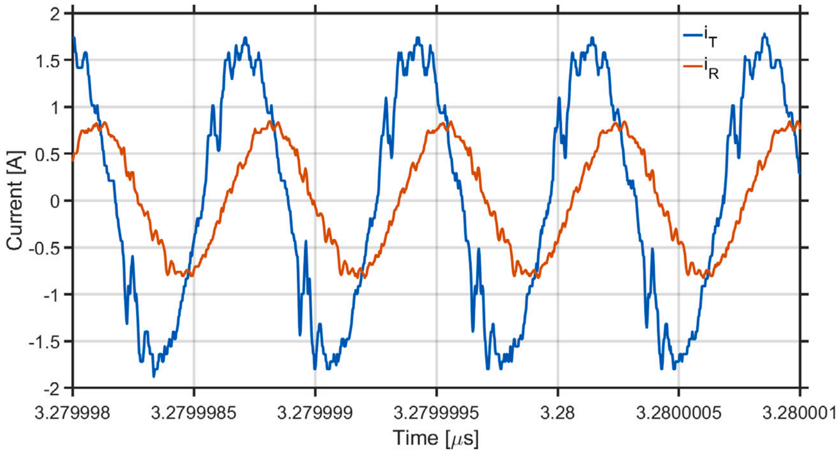

Fig. 10. The current on the transmitter side (i_T) and the receiver side (i_R).

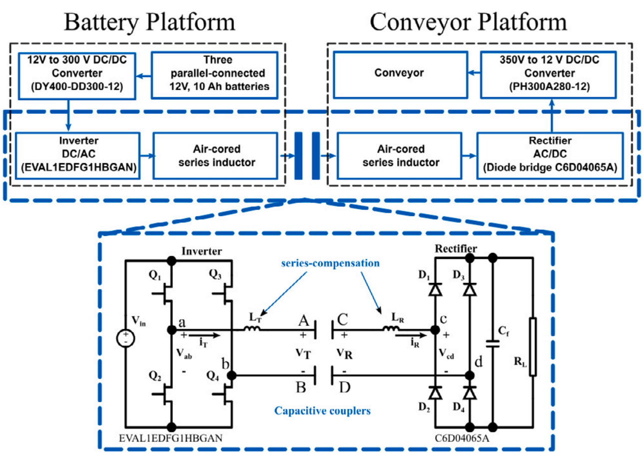

Fig. 11. The experimental setup.

distance. The efficiency decreases with the increase of the distance, which can be attributed to the sensitivity of the compensation circuits to the distance change. One way to enhance the efficiency of the system is by proposing control techniques to operate the inverter at a frequency that can adapt to the change in the distance. As further work, we will further improve the system efficiency and increase the transfer distance by proposing different resonant circuits. We will also investigate a control technique to achieve high efficiency with the variation of the separation distance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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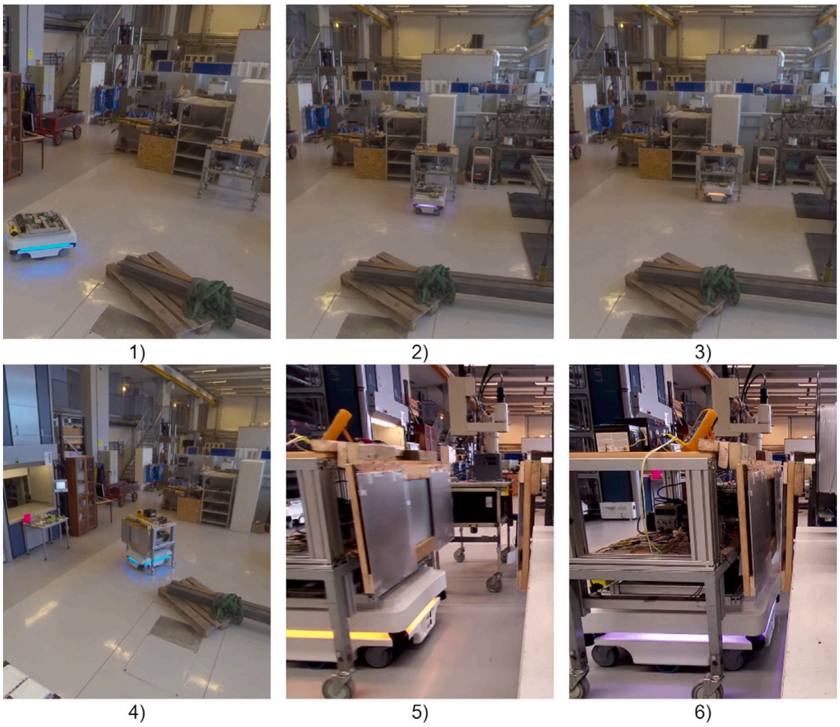

Fig. 12. Demonstration of how the CPT is implemented into the RMS: The mobile robot drives to pick up a full battery platform (step 1 to 4) and transports it to the charging RMS (step 5 to 6).

References

[1] Koren Y, Heisel U, Jovane F, Moriwaki T, Pritschow G, Ulsoy G, et al. Reconfigurable manufacturing systems. CIRP Ann 1999;48(2):527–40. http://dx.doi.org/10.1016/S0007-8506(07)63232-6.

[2] Bi ZM, Lang SYT, Shen W, Wang L. Reconfigurable manufacturing systems: the state of the art. Int J Prod Res 2008;46(4):967–92. http://dx.doi.org/10.1080/00207540600905646.

[3] Andersen A-L, Brunoe TD, Nielsen K, Rösiö C. Towards a generic design method for reconfigurable manufacturing systems: Analysis and synthesis of current design methods and evaluation of supportive tools. J Manuf Syst 2017;42:179–95. http://dx.doi.org/10.1016/j.jmsy.2016.11.006.

[4] Andersen A-L, Nielsen K, Brunoe TD. Prerequisites and barriers for the development of reconfigurable manufacturing systems for high speed ramp-up. Procedia CIRP 2016;51:7–12. http://dx.doi.org/10.1016/j.procir.2016.05.043.

[5] Rösiö C, Säfsten K. Reconfigurable production system design – theoretical and practical challenges. J. Manuf Technol Manag 2013;24:998–1018. http://dx.doi.org/10.1108/JMTM-02-2012-0021.

[6] Kim D-Y, Park J-W, Baek S, Park KB, Kim H-R, Park J-I, et al. A modular factory testbed for the rapid reconfiguration of manufacturing systems. J Intell Manuf 2020;31:661–80. http://dx.doi.org/10.1007/s10845-019-01471-2.

[7] Kovalenko I, Saez M, Barton K, Tilbury DM. SMART: A system-level manufacturing and automation research testbed. Smart Sustain Manuf Syst 2017;1:232–61. http://dx.doi.org/10.1520/SSMS20170006.

[8] Zühlke D. SmartFactory - towards a factory-of-things. Annu Rev Control 2010;34:129–38. http://dx.doi.org/10.1016/j.arcontrol.2010.02.008.

[9] Malik AA, Masood T, Kousar R. Reconfiguring and ramping-up ventilator production in the face of COVID-19: Can robots help? J Manuf Syst 2021;60:864–75.

[10] Arnarson H, Solvang B. Reconfigurable autonomous industrial mobile manipulator system. In: 2022 IEEE/SICE international symposium on system integration. 2022, p. 772–7. http://dx.doi.org/10.1109/SII52469.2022.9708887.

[11] Arnarson H, Mahdi H, Solvang B, Bremdal BA. Towards automatic configuration and programming of a manufacturing cell. J Manuf Syst 2022;64:225–35. http://dx.doi.org/10.1016/j.jmsy.2022.06.005.

[12] Radanovič P, Jereb J, Kovač I, Ude A. Design of a modular robotic workcell platform enabled by plug & produce connectors. In: 2021 20th international conference on advanced robotics. ICAR, 2021, p. 304–9. http://dx.doi.org/10.1109/ICAR53236.2021.9659345.

[13] ITU-R Recommendation ITU-R SM2110. Frequency ranges for operation of non-beam wireless power transmission systems. 2017, Available at https://www.itu.int/rec/R-REC-SM.2110-0-201709-S (2021/11/09).

[14] Alicia T-C, José M G-G, José A A. Wireless power transfer for electric vehicles: Foundations and design approach. 1st ed. Springer International Publishing: Imprint: Springer; 2020.

[15] Ahmad A, Alam MS, Chabaan R. A comprehensive review of wireless charging technologies for electric vehicles. IEEE Trans Transp Electr 2018;4(1):38–63. http://dx.doi.org/10.1109/TTE.2017.2771619.

[16] Liu W, Chau KT, Lee CHT, Han W, Tian X, Lam WH. Full-range soft-switching pulse frequency modulated wireless power transfer. IEEE Trans Power Electron 2020;35(6):6533–47. http://dx.doi.org/10.1109/TPEL.2019.2952573.

[17] Lu F, Zhang H, Mi C. A review on the recent development of capacitive wireless power transfer technology. Energies 2017;10(11). http://dx.doi.org/10.3390/en10111752, URL https://www.mdpi.com/1996-1073/10/11/1752.

[18] Zheng C, Ma H, Lai J-S, Zhang L. Design considerations to reduce gap variation and misalignment effects for the inductive power transfer system. IEEE Trans Power Electron 2015;30(11):6108–19. http://dx.doi.org/10.1109/TPEL.2015.2424893.

[19] Hossain A, Darvish P, Mekhilef S, Tey KS, Tong CW. A new coil structure of dual transmitters and dual receivers with integrated decoupling coils for increasing power transfer and misalignment tolerance of wireless EV charging system. IEEE Trans Ind Electron 2022;69(8):7869–78. http://dx.doi.org/10.1109/TIE.2021.3108697.

[20] Zhang H, Lu F, Hofmann H, Liu W, Mi CC. Six-plate capacitive coupler to reduce electric field emission in large air-gap capacitive power transfer. IEEE Trans Power Electron 2018;33(1):665–75. http://dx.doi.org/10.1109/TPEL.2017.2662583.

[21] Esser A, Skudelny H-C. A new approach to power supplies for robots. IEEE Trans Ind Appl 1991;27(5):872–5. http://dx.doi.org/10.1109/28.90341.

[22] Hirai J, Kim T-W, Kawamura A. Practical study on wireless transmission of power and information for autonomous decentralized manufacturing system. IEEE Trans Ind Electron 1999;46(2):349–59. http://dx.doi.org/10.1109/41.753774.

[23] Han W, Chau KT, Hua Z, Pang H. Compact wireless motor drive using orthogonal bipolar coils for coordinated operation of robotic arms. IEEE Trans Magn 2022;58(2):1–8. http://dx.doi.org/10.1109/TMAG.2021.3082018.

[24] Kikuchi S, Sakata T, Takahashi E, Kanno H. Development of wireless power transfer system for robot arm with rotary and linear movement. In: 2016 IEEE international conference on advanced intelligent mechatronics. 2016, p. 1616–21. http://dx.doi.org/10.1109/AIM.2016.7577001.

[25] Tokano K, Zhu W, Osato T, Nguyen K, Sekiya H. Optimal design of 6.78 MHz wireless power transfer system for robot arm. In: 2021 IEEE international symposium on circuits and systems. 2021, p. 1–5. http://dx.doi.org/10.1109/ISCAS51556.2021.9401073.

[26] Wu J, Dai X, Gao R, Jiang J. A coupling mechanism with multidegree freedom for bidirectional multistage WPT system. IEEE Trans Power Electron 2021;36(2):1376–87. http://dx.doi.org/10.1109/TPEL.2020.3010955.

[27] Covic GA, Boys JT. Inductive power transfer. Proc IEEE 2013;101(6):1276–89. http://dx.doi.org/10.1109/JPROC.2013.2244536.

[28] Zhang Z, Zhang B. Omnidirectional and efficient wireless power transfer system for logistic robots. IEEE Access 2020;8:13683–93. http://dx.doi.org/10.1109/ACCESS.2020.2966225.

[29] Lee ES, Kim MY, Kang SM, Han SH. Segmented IPT coil design for continuous multiple charging of an electrified monorail system. IEEE Trans Power Electron 2022;37(3):3636–49. http://dx.doi.org/10.1109/TPEL.2021.3115511.

[30] Zhang Y, Yang J, Jiang D, Li D, Qu R. Design, manufacture, and test of a rotary transformer for contactless power transfer system. IEEE Trans Magn 2022;58(2):1–6. http://dx.doi.org/10.1109/TMAG.2021.3094135.

[31] TDKCo. Magnetic resonance method of wireless power transfer technology for industrial equipment. 2022, URL https://product.tdk.com/en/techlibrary/developing/wireless/index.html. [Online; Accessed 25 May 2022].

[32] Waypoint Robotics. EnZone™ — Wireless charging and energy on demand. 2022, URL https://waypointrobotics.com/enzone-wireless-power-system/. [Online; Accessed 25 May 2022].

[33] Delta Co. MOOVair 1 kW wireless charging system. 2022, URL https://www.deltaww.com/en-US/products/Industrial-Battery-Charging/5776. [Online; Accessed 25 May 2022].

[34] GaN system. WiBotic autonomous charging. 2022, URL https://gansystems.com/gan-applications/wibotic-300-w-wireless-power-system/. [Online; Accessed 25 May 2022].

[35] Arnarson H. Super flexible reconfigurable manufacturing system (5x speed). 2022, URL https://youtu.be/UXUlaawd8Ps. [Online; Accessed 21 Feb 2022].

[36] CoolGaN. High-frequency half-bridge evaluation board featuring EiceDRIVER™ GaN. 2022, URL https://www.infineon.com/cms/en/product/evaluation-boards/eval_1edf_g1b_hb_gan/. [Online; Accessed 25 May 2022].

[37] Wolfspeed. Silicon Carbide Schottky Diode. 2022, URL https://assets.wolfspeed.com/uploads/2020/12/C6D04065A.pdf. [Online; Accessed 25 May 2022].

Paper 7

Towards smart layout design for a reconfigurable manufacturing system

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Author's Contribution

Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

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Towards smart layout design for a reconfigurable manufacturing system

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ABSTRACT

Global competition and increased variety in products have created challenges for manufacturing companies. One solution to handle the variety in production is to use reconfigurable manufacturing systems (RMS). These are modular systems where machines can be rearranged depending on what is being manufactured. However, implementing a rearrangeable system drastically increases complexity, among which one challenge with RMS is how to design a new layout for a customized product in a highly autonomous and responsive fashion, known as the layout design problem. In this paper, we combine several Industry 4.0 technologies, i.e., IIoT, digital twin, simulation, advanced robotics, and artificial intelligence (AI), together with optimization to create a smart layout design system for RMS. The system automates the layout design process of RMS and removes the need for humans to design a new layout of the system.

1. Introduction

With a global market and interconnected supply chains, the competition between manufacturing companies has risen substantially. In addition, the product life cycle has become shorter and the manufacturing industry is moving from mass production towards mass customization and mass personalization. This means that manufacturing systems need to be changed so that they can better adapt to the changes in the market and capture new business opportunities. Therefore, there is a need for a manufacturing system that can be easily changed and scaled up or down depending on the various demands of consumers.

To solve these problems, Koren et al. [1] proposed the idea of a reconfigurable manufacturing system (RMS). An RMS can be described as a manufacturing system that can be changed and adjusted by rearranging and changing the components. They are designed for the reconfiguration of both hardware and software components in the system [2].

However, having a system that can be rapidly reconfigured adds new challenges and complexity to the system [3]. One of the challenges with RMS is the layout problem. The layout problem focuses on how to design/rearrange the RMS, when considering both the capacity and operational performance of the system [4]. To be able to reconfigure the manufacturing system quickly, it would be beneficial to give the exact placement of the machines to minimize the reconfiguration time of the RMS. In addition, when a new customized order comes, planning and designing a new product-based layout for an RMS is a time-consuming job that requires a significant amount of human labor and input.

There is, however, a lack of research on the layout problem for RMS. Sabioni et al. [5] reveal that most papers that work on the layout problem for RMS, focus on cost minimization, and there are few papers that focus on the design optimization problem. Thus, there is a need for a model that can support the redesign of the layouts [6]. One method to solve the layout problem can be to implement other tools/technologies that can help in the design. Maganha et al. [6], note that there are few investigations on supportive tools for RMS design.

Industry 4.0 is the next technological revolution and brings several cutting-edge technologies such as big data, industrial internet of things (IIoT), simulation, cloud computing and cyber–physical systems. These technologies are important for the success of RMS [7] and can be used to further automate the systems. However, Brotolini et al. [8] indicate that there is a lack of research on implementing and using Industry 4.0 technologies in RMS.

Applying digital twins and simulation enables a faster method that allows for testing, optimization, development, and deployment of new layouts for the RMS [9]. Maganha et al. [6] note that there is a need to investigate the use of simulation to design manufacturing facilities since simulation tools can be used to test the performance of the system

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in a more realistic way. In addition, industry 4.0 technologies can be used to achieve smart layout design of the RMS [6]. In this paper, we will define smart layout design, as combining multiple Industry 4.0 technologies to solve the layout problem in an automatic manner.

Arnarson et al. [10] propose an RMS that uses a mobile robot to reconfigure the system automatically without any human intervention. In the paper, they showed that different placement of the platforms in an RMS gives different manufacturing times. It is therefore important to minimize the distance the manufactured part has to move in the system. This paper also reveals that designing and rearranging an RMS can be extremely time-consuming and usually requires a large amount of human labor and input, so there is a need for a method to design the layout of the manufacturing system automatically.

In the literature, there are few papers on combining multiple industry 4.0 technologies together to solve the layout design problem for RMS. To fill this gap, in this paper, we implement several industry 4.0 technologies such as IIoT, digital twin/model, simulation, advanced robotics, and artificial intelligence (AI) with optimization to develop a smart layout design system for RMS. Furthermore, we use evolutionary computations, known as a subfield of AI, where a population-based algorithm produces a population of candidates that evolves toward an optimal or near-optimal solution [11]

More specifically, we formulate a mathematical model for the platform-based RMS proposed by Arnarson [10] and use optimization to find a layout automatically. From the optimization, a digital model is generated, which can be tested with simulation for further validation of the system. Finally, the system is tested on a physical RMS to verify and validate if the layout optimization with a digital model simulation can work effectively and correctly in the real-world system.

The main contributions of the work are as follows:

- Investigate how Industry 4.0 technologies such as IIoT, digital model, simulation, and advanced robotics can be combined with optimization to create smart layout design for RMS.
- Develop a mathematical model which gives the exact position/coordinates of a platform-based RMS.
- Use AI and evolutionary computations to search/optimize for a layout configuration for the platform-based RMS.
- Generate a digital model automatically from the solution of the optimization.
- Connect the optimization program together with the digital model simulation software for further testing and validation in a digital environment.
- Use IIoT technology to connect the optimization, digital model simulation, and a physical RMS together for communication.

The rest of the paper is structured as follows: Section 2 reviews previous studies on the layout design problem for RMS. Section 3 develops the mathematical model of the system, and Section 4 looks at the implementation and the results from the system. Finally, we discuss the results in Section 5 and conclude the paper in Section 6.

2. Prevous studies

2.1. Facility layout problem

In more broad research, the layout design problem for manufacturing systems in general is referred to as the facility layout problem [12]. Besbes et al. [13] looked at the layout facility problem, where they arranged facilities on a planar site and considered geometric constraints for the facilities. They tested the system using the proposed algorithm to optimize eight facilities on the plan floor. Lim et al. [14] evaluated hybrid algorithms, where they used the algorithms for layout optimization of multi-cellular manufacturing systems.

Guo et al. [15] used a digital twin to optimize the manufacturing workshop. A digital twin was used to optimize different parts of the workshop and the distribution routes. The method was tested in a physical welding workshop, which resulted in an increased production capacity of 29.4%. This shows the potential of implementing digital twins when doing optimizations of the layout. The authors also mention that there is a lack of research on using digital twins with layout optimization, and for further research, more methods should be developed for layout optimization using digital twins.

Moreover, in a literature review on the facility layout problem [16] reveals that most researchers did not include simulation and safety drivers with the facility layout design problem. They also noted that there was less focus on industry 4.0 technologies such as IIoT and digital twin. Zubaidi et al. [16] note that implementing elements of industry 4.0 can help in creating a more reliable, comprehensive, and sustainable layout design. It is also important to note that the facility layout problem is often considered a static problem. In contrast, the layout problem for RMS is a dynamic problem since the RMS layout is made to be changed. Since it is a dynamic problem, it requires powerful and flexible simulation tools.

2.2. Layout design of RMS

Layout design for RMS encompasses many elements, including process planning [17,18], scheduling [19], scalability planning [20], and cost optimization [21–24]. There are, however, fewer papers that look at the placement of the machines.

Koren et al. [2] proposed a method on how to design an RMS. Their method requires planning, and if the RMS has many processes and machines, the problem will become more complex. They also mention that each new product that is manufactured should include a new design of the RMS. Guan et al. [25] investigated the layout design for RMS where they considered automated guided vehicles for material handling instead of using conveyors. In the study, precedence graphs are used to show the flow and positions of the workstation.

Haddou Benderbal et al. [26] studied the machine layout problem for RMS, where they developed a system that could propose the best placement for the machines. In addition, Haddou Benderbal et al. [27] also developed a decision-support approach for switching between products in the same product family. However, in both cases, the machines could only be placed in predefined positions.

Another paper from Besbes et al. [28] investigated the facility layout problem for RMS. In the study, the goal was to minimize the material handling cost. The layout was generated with a genetic algorithm, and then an A* search algorithm was used to find the shortest distance between manufacturing cells. Nevertheless, the authors mention that the method is tested offline and for further work, the system should be tested on a physical RMS system. In addition, they mention that the model should be expanded toward a multi-objective problem that considers the shape and orientation of the manufacturing cells.

There are few examples of systems that can generate a layout for the RMS. Abdelkrim et al. [12] note that there were few researchers working on solving the layout design problem for RMS. From a literature review, Sabioni et al. [5] reveal that most papers working on optimizing of RMS configurations looked at cost minimization. The study did not find any relevant researches that combined both the layout design and machine configuration problem at the same time. It is also noted that it is difficult to find industries or laboratories that have implemented an RMS.

2.3. Simulation for layout design

A few attempts have been made to implement industry 4.0 tools, such as simulation and digital twin, to solve the layout design problem. Yamada [29] used 3D simulation to do analysis and design evaluation for the reconfiguration of an RMS. In the study, he looked at a manufacturing system with transport robots, input stations, output stations, movable manufacturing cells and processes, where he tried to minimize the manufacturing time using particle swarm optimization. The simulation is rather simple, where the manufacturing cells and other stations are modeled in the simulation as circles and squares. Zheng et al. [30] proposed a simulation framework for the layout, cost, and performance of the system. They used the simulation tool "Plant Simulation", which is a discrete-event simulator, to analyze the behavior of a system. Petroodi et al. [31] used a discrete event simulation tool (Simul8) together with optimization to solve the resource allocation and production planning problem. These studies show the potential of combining simulation and optimization together. However, these examples of using simulations are simple and are not validated with a real RMS.

Work has also been done on using 3D manufacturing simulations and digital twins to support the layout design process. Santos et al. [32] used a simulation-based approach to support the design and operational management of the system. The simulation allowed the planner to test different configurations and layouts virtually. Touckla et al. [33] proposed a framework with a digital twin design and simulation model for RMS. These studies do not use optimization to create the layout and require human operators to design the system.

There is also research on using digital twins for planning in RMS. Leng et al. [34] proposed a digital twin for fast reconfiguration of RMS, which was used as a tool to shorten the time of production changeover. Kurniadi et al. [35] investigated the use of digital twin simulation for reconfiguration planning. They used both discrete-event simulation (DES) and visual simulation to show that digital twins can help effectively integrate RMS into a production system. The RMS digital twin framework proposed by Hajjem et al. [36] suggested that using digital twins with RMS provides improved functionalities, e.g., simulation and intelligent sensors, which can improve the system's intelligence and efficiency.

2.4. Summary

All the papers investigating the layout design problem for RMS have not tested their system or method on a physical RMS to validate if the system works. Rosio et al. [3] did also find limited examples of industrial examples of RMS, and there is a lack of knowledge on how to design an RMS.

In addition, there is a lack in the literature on exploiting the benefits of using Industry 4.0 technologies to solve the layout design problem of RMS. These existing studies have clearly shown the potential of using simulation and digital models for the layout design problem, but there is a need for more investigation, for instance, by combining both optimization and simulation. In addition, there are a few examples showing how Industry 4.0 technologies such as digital twins and simulation can be implemented in a physical RMS. Integrating various industry 4.0 technologies can lead to a smart layout design system for RMS which can automate the layout design process.

3. Mathematical model

In this project, a mathematical model is formulated based on the concept of a modular platform based RMS described in [10]. This type of system has multiple modular platforms that can easily be added or removed depending on the demand or what is being manufactured. The goal is to develop a general mathematical model which can be used to automatically generate layouts for a platform based RMS.

3.1. Assumptions

To develop the mathematical model, the following assumptions are made:

1. The mathematical model is a 2D plane, and the 3D dimension is not considered.

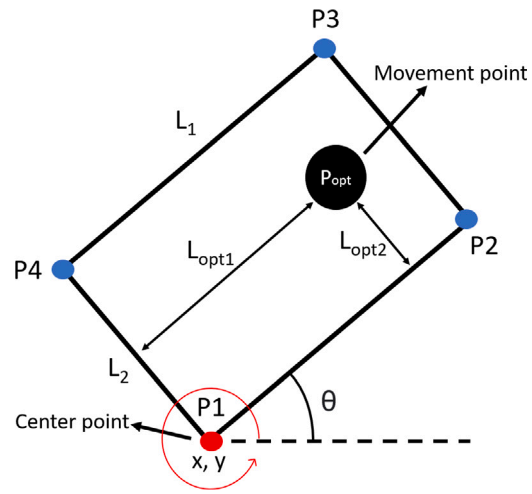

Fig. 1. The center point and movement point of the platforms. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2. All platforms are modeled as rectangles
3. The platforms can be placed in a space of 10 × 10 m
4. All manufactured parts move from a singular point on the platforms.
5. The amount of platforms is given, and the model can use all platforms to design the layout. There is a risk of the layout becoming chaotic if too many platforms of the same type are used.
6. All platforms are made to be the same- or similar height.

3.2. Describe the platforms

Manufacturing systems usually contain different machines depending on the tasks. In the system, each platform can contain a 3D printer, a CNC machine, a conveyor or a robot arm. To categorize these platforms and be able to generalize the system, we divide the platforms into four categories:

- Input platform: A platform that gives material to the system, or an input part of the system
- Movement platform: A platform that is used to move parts between platforms (can be robot arms or humans).
- Work platform: A platform used to do a process, such as quality control, machining process, and assembly station.
- Output platform: A platform that moves the parts out of the system (can be conveyors).

Each of the platforms has three variables used in the optimization, x and y for the position and theta for the rotation of the platform. The platforms do also have size variables and the position of the movement points.

The point of rotation (center point) is highlighted with the red circle as shown in Fig. 1. In this project, we test two types of rotations for theta. The first type sets a fixed 0, 90, 180, or 270 degrees rotation for the platforms and the second type uses a number between 0–360 for theta.

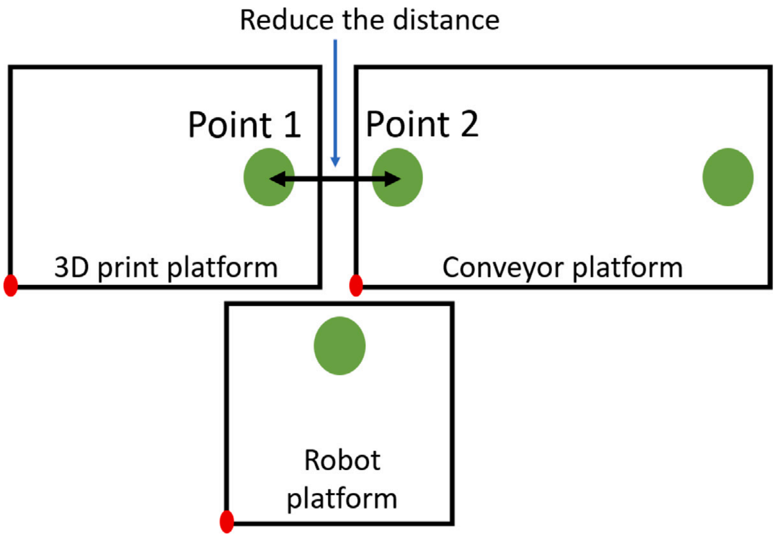

Fig. 2. Demonstration of a simplified RMS with three platforms.

To calculate the x and y positions of the corners (P2-P4) the following formulas are used when theta:

$$
\begin{aligned}
P1_x &= x \\
P1_y &= y \\
P2_x &= L_1 * cos(\theta) + x \\
P2_y &= L_1 * sin(\theta) + y \\
P3_x &= L_1 * cos(\theta) - L_2 * sin(\theta) + x \\
P3_y &= L_1 * sin(\theta) + L_2 * cos(\theta) + y \\
P4_x &= -L_2 * cos(\theta) + x \\
P4_y &= L_2 * sin(\theta) + y \\
Popt_x &= L_{opt1} * cos(\theta) - L_{opt2} * sin(\theta) + x \\
Popt_y &= L_{opt1} * sin(\theta) + L_{opt2} * cos(\theta) + y
\end{aligned}
\tag{1}
$$

3.3. Optimization problem

In this paper, we investigate a platform-based RMS, and the optimization goal is to improve efficiency by minimizing the total movement distance of the workpiece throughout the system. Since the movement distance on each working platform is fixed, the problem becomes thus the minimization of the distance between different platforms. Fig. 2 illustrates a simple case with a 3D printer, a robot platform, and a conveyor. In this example, we try to minimize the distance between the 3D printer and the conveyor, say, the distance between point A and point B. At this stage, the distance between the robot platform (movement platform) and the other platforms is not considered, because the robot platform only moves the parts from one working platform to another. The only requirement for the robot platform is that it can reach the required points on the respective working platforms.

Thus, the objective of the optimization model is to minimize the Euclidean distance for moving the workpiece between point 1 and point 2, as shown in Eq. (2):

$$Minimize\ OBJ = \sqrt{(x_{point1} - x_{point2})^2 + (y_{point1} - y_{point2})^2} \tag{2}$$

$$Minimize\ Obj1 = \sum_{i \in M} \sum_{j \in M} d_{ij} c_{ij} wtij \tag{3}$$

Moreover, the Euclidean distances are calculated from a given order/sequence of the platforms in the system. We generalize the mathematical optimization model in Eq. (3), which minimizes the total movement distance (c_{ij}) of the workpiece throughout the whole RMS. The set of working platforms is defined by $M = \{1, 2, \ldots, m\}$, and calculate the movement distance between two working platforms, where $i, j \in M$ and $i \neq j$.

In an RMS for mass and/or individualized customization, the manufacturing procedures need to be formulated based on the requirements of specific products or product families. In this regard, c_{ij} is a binary parameter establishing the linkage and precedence between two working platforms in the RMS, which is determined based on a specific product. If the system uses multiple input and output platforms, the optimization model considers all combinations of how the part can move in the system. For instance, Fig. 3 shows an RMS system that has two 3D print platforms, working platforms, and conveyor platforms, where five linkages are established by setting c_{13}, c_{23}, c_{34}, c_{45}, and c_{46} equal to 1.

In this model, wt_{ij} is the weight of each linkage, which may help to adjust the movement distance (c_{ij}) with, for example, the flow of workpieces between two working platforms. Besides, it can also be used to solve the challenges related to a multi-platform RMS system. As shown in Fig. 4, a manufacturing system can be divided into multiple platforms. In this example, the system is divided into three platforms, where two conveyor platforms are used to connect these platforms. One challenge of having a conveyor between two platforms is that, in the optimization process, the two platforms are likely to fight for the same conveyor. Moving the conveyor in either direction may yield the same optimal result, and the conveyor may be placed in between the two platforms, which are far away from each other, as can be seen in Fig. 5. There are several ways to solve this problem. One method is to add a larger weight to the conveyor's output and input, which can help to reduce the distance between the two platforms connected by the same conveyor. This method has little impact on the rest of the system.

Next, we consider the optimal positions of movement platforms. For this system, we model the movement platforms as robot arms and will therefore need to take into consideration the reach of the robot arms in the mathematical model. As mentioned in Section 3.1, the mathematical model is based on a 2D plane. However, the robot arms have a circular reach in all axis. This means that if the platforms are of different heights, the robot arms might not be able to reach the platforms while being within the radius of the 2D plane. In this system, we assume that all platforms are at the same or similar height, and we will therefore model the reach of the robot arm as a circular radius, as shown in Fig. 6. It should be noted that the robot might still not be able to reach certain points with a particular orientation (yaw, pitch, and roll) of the tool center point. As a result, a simulation is used for further verification if the robot arm is capable of picking the item (Section 4.2).

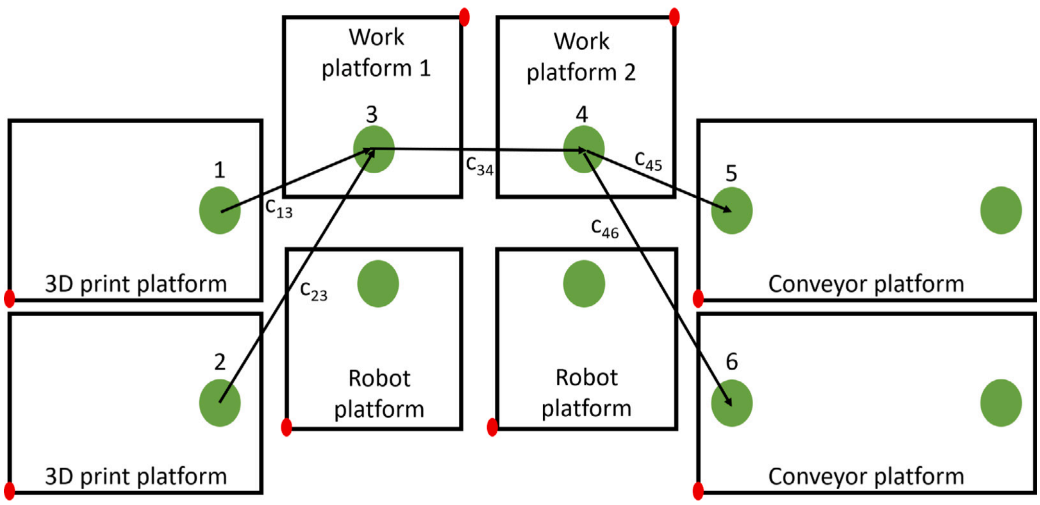

Fig. 3. A RMS with two input platforms, two working platforms, two output platforms, and two movement platforms.

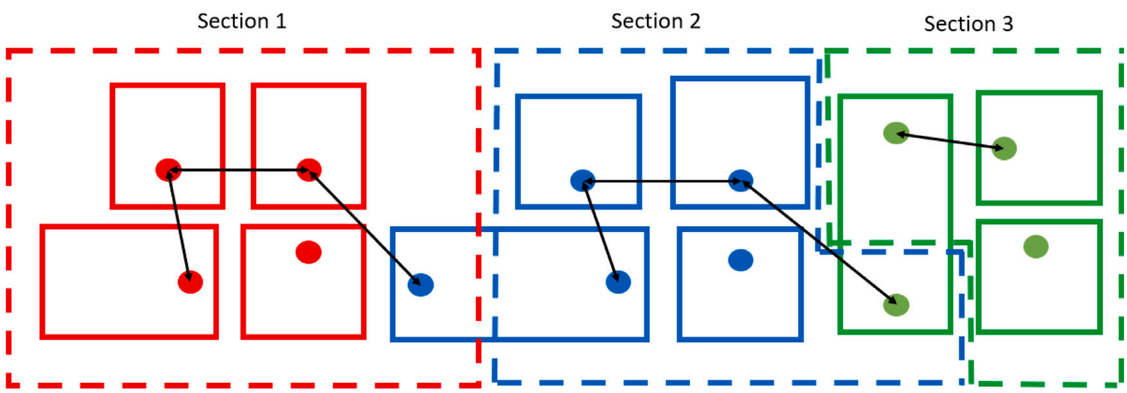

Fig. 4. A multi-platform RMS system.

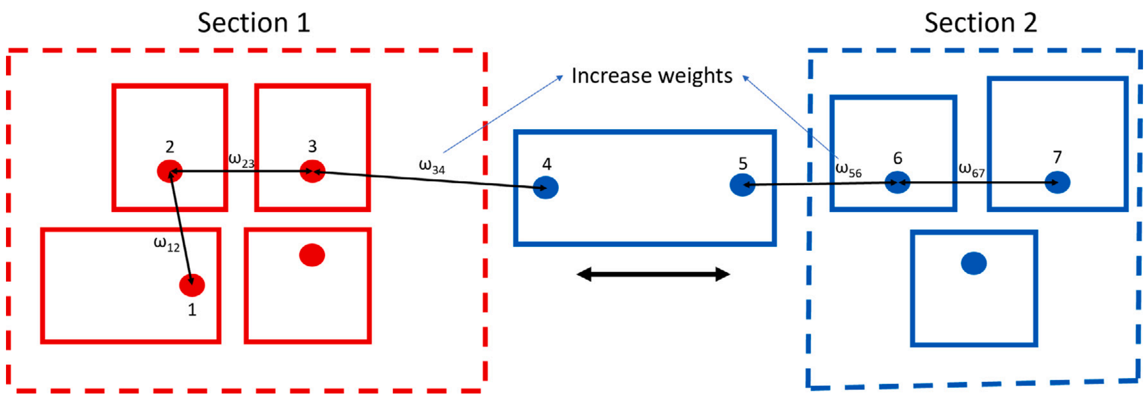

Fig. 5. Illustration of the optimization challenge related to a multi-platform RMS with shared conveyors connecting different platforms.

The total movement distance of the robot arms needs to be minimized, while at the same time, all the working platforms need to be assigned to a robot arm within its maximum reachable radius. Mathematically, the following constraint (4) needs to be held. Herein, the set of movement platforms is given by $N = 1, 2, \ldots, n$, and r_n is the maximum reachable radius of each movement platform. Moreover, a_{nm} is a binary variable that determines if a working platform is assigned to a movement platform, and p_{nm} is the movement distance (c_{ij}) between them.

$$p_{nm} \leq r_n a_{nm}, \forall\, n \in N, m \in M \tag{4}$$

Besides, each working platform must be served by a robot arm, as shown in Eq. (5):

$$\sum_{n \in N} a_{nm} = 1, \forall\, m \in M \tag{5}$$

However, the use of this non-linear hard constraint drastically increases the computational efforts needed to solve the optimization model. Thus, in this paper, it is converted to a soft constraint to improve the computational efficiency to find near-optimal solutions. These solutions will be further validated in the simulation stage, which helps to effectively eliminate all the infeasible solutions. To implement the soft constraint, we introduce a piecewise function in Fig. 7 to

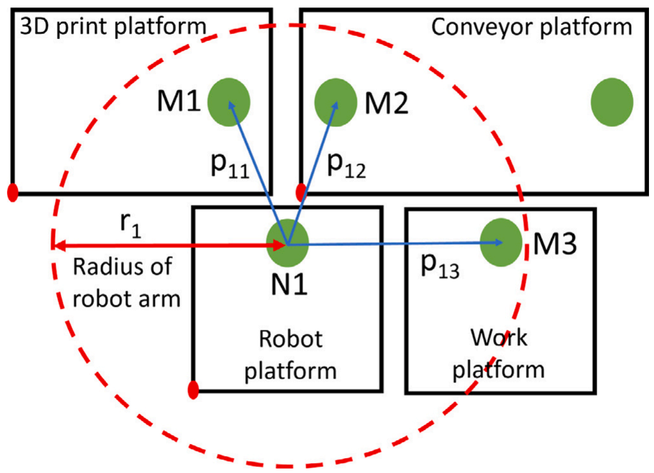

Fig. 6. Illustration of the maximum reachable radius of the robot platform.

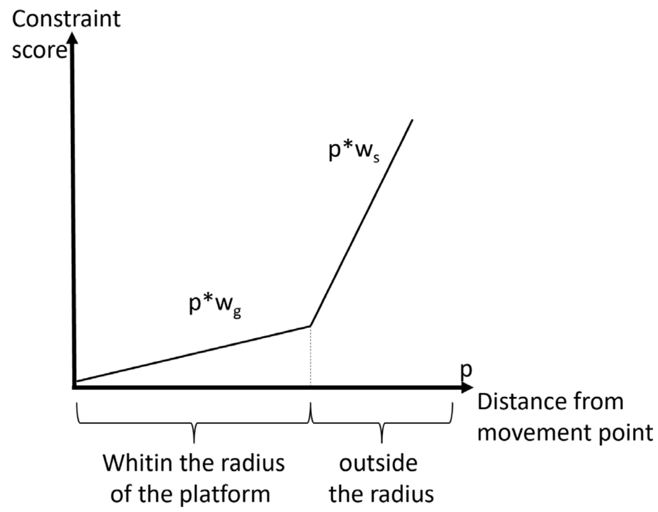

Fig. 7. Piecewise function for weight calculation.

calculate the weight of the movement distance between robot arms and working platforms. As shown, if the robot arm can reach the required points, the weight on the respective distance is very small. However, if the robot arm cannot reach the required point, a higher weight will be given as a penalty for the respective linkage between the robot arm and the working platform, which will, in most cases, lead to $a_{nm} = 0$. An illustration of how the weights can be seen in Fig. 8. The general form of the second objective as well as the respective constraint is given in Eq. (6).

$$Minimize\ Obj2 = \sum_{m\in M}\sum_{n\in N} p_{nm} a_{nm} wp_{nm} \tag{6}$$

Subject to:

$$\sum_{n\in N} a_{nm} = 1, \forall\ m \in M$$
$$wp_{nm} = \begin{cases} p_{nm} w_g, & \text{if } P_{nm} \le r_n \\ p_{nm} w_s, & \text{if } P_{nm} \ge r_n \end{cases} \tag{7}$$

There is also a need to consider the rotation and reachable area of different types of robot arms. For instance, Universal Robots has a reach of ±360 degrees, while a Nachi MZ07 has a reach of ±170 degrees. As shown in Fig. 9, the unreachable area of the robot arm can be drawn as a triangle. A check is thus added to see if any required points on the working platforms are in the unreachable area of the robot arms. First, all the points in the triangle are calculated with the following formulas:

$$\begin{aligned} c_n^1 &= (x_{2(n)} - x_{1(n)}) \times (y_{p(m)} - y_{1(n)}) - (y_{2(n)} - y_{1(n)}) \times (x_{p(m)} - x_{1(n)}) \\ c_n^2 &= (x_{3(n)} - x_{2(n)}) \times (y_{p(m)} - y_{2(n)}) - (y_{3(n)} - y_{2(n)}) \times (x_{p(m)} - x_{2(n)}) \\ c_n^3 &= (x_{1(n)} - x_{3(n)}) \times (y_{p(m)} - y_{3(n)}) - (y_{1(n)} - y_{3(n)}) \times (x_{p(m)} - x_{3(n)}) \end{aligned} \tag{8}$$

A constant k_n is added to increase the length of the triangle to ensure the whole area is checked. For the Nachi MZ07 robot arm, the constant is 1.2. In addition, all robot arms are 90 degrees rotated on the platforms, and we therefore add 90 degrees. Using these points, we check with Eq. (8) if the point p on the working platform m is inside the triangle with these conditions when $a_{nm} = 1$:

If the point is inside the triangle, a higher penalty should be applied. In addition, in some cases, one movement platform is able to reach all the required platforms, and then there would be no need for another movement platform that is not assigned to any working platforms, as shown in Fig. 10. The redundant movement platform needs thus to be eliminated from the system.

The general form of the mathematical optimization model is then given in Eq. (9):

$$\begin{aligned} &Minimize\ Obj1 = \sum_{i\in M}\sum_{j\in M} d_{ij} c_{ij} wtij \\ &Minimize\ Obj2 = \sum_{m\in M}\sum_{n\in N} p_{nm} a_{nm} wp_{nm} \end{aligned} \tag{9}$$

Subject to Eq. (10):

$$\sum_{n\in N} a_{nm} = 1, \forall\ m \in M$$

$$wp_{nm} = \begin{cases} p_{nm} w_s, if\, wp_{nm} = 1 \text{ and if}\{p_{nm} \ge r_n\} \text{ or} \\ \quad \begin{cases} P_{nm} \le r_n \text{ and } \begin{cases} C_n^1 \ge 0 \text{ and } C_n^2 \ge 0 \text{ and } C_n^3 \ge 0 \\ \text{or } C_n^1 \le 0 \text{ and } C_n^2 \le 0 \text{ and } C_n^3 \le 0 \end{cases} \end{cases} \\ p_{nm} w_g, \text{otherwise} \end{cases} \tag{10}$$

Finally, another hard constraint needs to be added to ensure the model is not to have any overlap between different platforms. One method to formulate this constraint is to use the separating axis theorem (SAT). The SAT can be used with any convex shapes to check if there is any overlap. For each of the solutions generated, the SAT is tested. If there is an overlap between the platforms, the solution is eliminated, and only the solutions without overlap are considered.

4. Implementation

4.1. Solve mathematical model

One of the challenges with RMS is the complexity of such systems. Increasing the number of platforms in the system also increases the number of possible layouts for the system. One method to find a layout for the RMS is to use evolutionary computation, which is a sub-field of AI. Evolutionary computation uses population based algorithms, where a population is maintained and evolves towards a good/optimal solution [11].

For this project, we used non-dominated sorting genetic algorithm 2 (NSGA2) [37] for the optimization since it is a powerful multi-objective algorithm [38], which has been widely used to solve process planning problems [38] for RMS design. Due to its reliability and speed, the NSGA2 has been used to solve workshop-related problems [39], allocation problems, scheduling problems, traveling salesman problems, and vehicle routing problems [40]. The NSGA2 is a multiobjective evolutionary algorithm that can find multiple Pareto-optimal solutions.

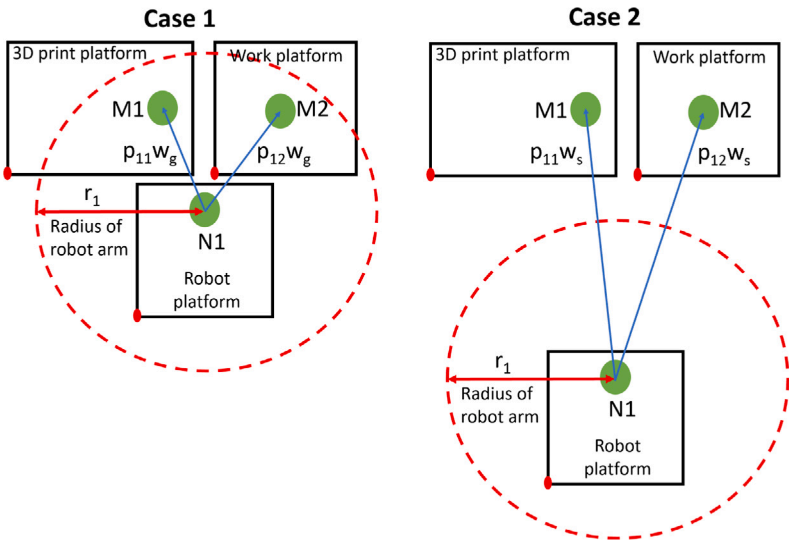

Fig. 8. Example of the Piecewise function for weight works. In case 1 the robot platform can reach the platforms and the w_g weight is used, while in case 2 the robot platform cant reach the points and the w_s is used.

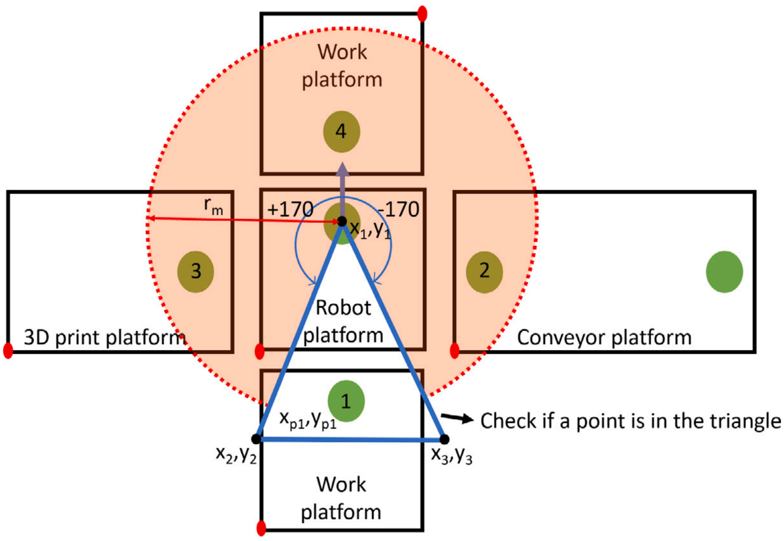

Fig. 9. Illustration of the reachable area for a robot arm, where the blind zone of the robot arm is shown.

It is an improvement on NSGA in terms of computational complexity, the need to specify sharing parameters and the lack of elitism [37].

The NSGA2 algorithm is implemented in python using the library Pymoo [41] and a flowchart of the algorithm can be seen in Fig. 11.

The input to the system is a list with all platforms in each section. For example, if a section contains *"3D printer, Robot platform, Work Table - 1, Conveyor out"*, then a part will move from the 3D printing platform to the work table - 1 to do a process and move out of the section with the conveyor platform. The robot platform is used to move the parts between the platforms. Fig. 12 shows the input to the system and the resulting layout.

The list is used to determine how the manufactured parts move through the system and the size of each platform. Then, the mathematical model is used for optimization with NSGA2 to find a layout.

In this project Pymoo 0.5.0 is used, and the optimization is executed on an AMD Ryzen 9 3950X processor.

A video example of when the layout optimization is running can be seen at https://youtu.be/UNsugBOi4cs. The video shows the best solution for each generation.

4.2. Digital model, simulation, and IIoT

It is difficult to describe and include all restrictions in a mathematical model. Making the model too complex can also make the problem unsolvable. It can therefore be beneficial to have a simpler mathematical model and connect the solution generated from the mathematical model with simulation tools, as a second layer to validate/test the solution. For this purpose, Visual Components Premium 4.4 [42] is used. Visual Components is a visual simulation software used to design and optimize manufacturing systems. It is possible to use Visual Components both for developing a visual digital model of the system, as well as for running manufacturing simulations. Hence, Visual Components is used to generate a digital model from the optimization, and then the digital model is used to run the simulation.

There is also a need for communication between all parts of the system. Since the system is made to be flexible, where the platforms can be moved to any position in the manufacturing environment. One method to allow for communication in a system is to use IIoT. IIoT is an extension of IoT in industrial applications and has a strong focus on machine-to-machine communication [43]. It is therefore used

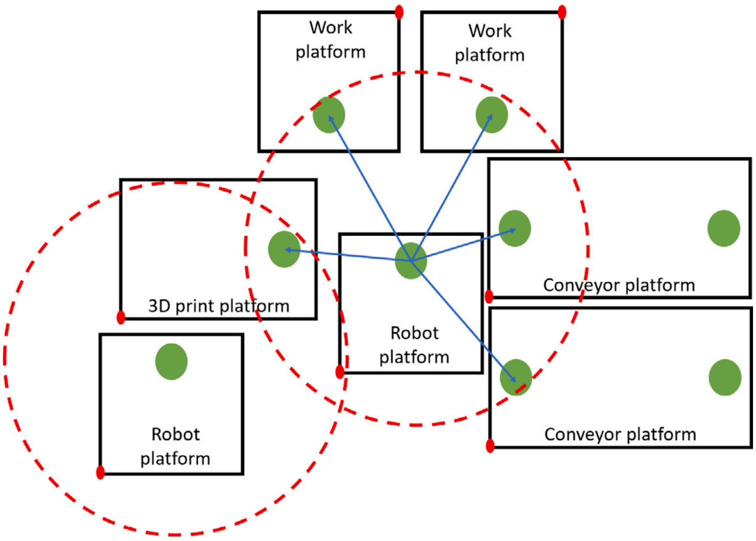

Fig. 10. Illustration of one robot arm that can move parts between all platforms, while the last robot arm cant perform any tasks.

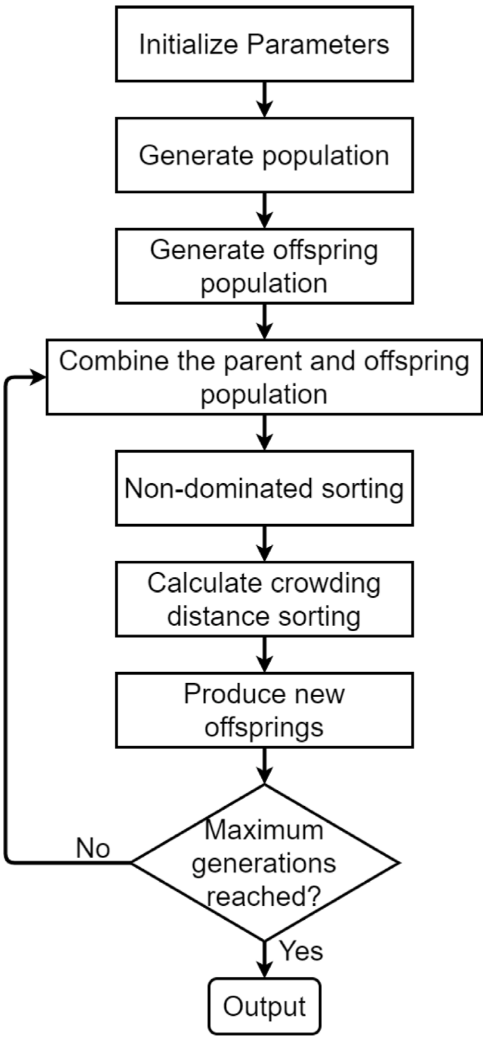

Fig. 11. A flowchart of the NSGA2 algorithm.

for communication with the platforms in the system and control the mobile robots. IIoT can also be used to transfer the layout to the mobile robot for automatic configuration of the system. In this system, the Open Platform Communications Unified Architecture (OPC UA) is used for IIoT. The OPC UA is an IEC 62541 standard, often used for communication between industrial equipment [44]. In addition, Visual Components support connectivity functions such as OPC UA and can therefore be used to connect the optimization simulation and physical system together.

The layout program in python is therefore connected to an OPC UA server, where the solution from the optimization is directly sent over to Visual Components. An illustration of how the system is connected and setup can be seen in Fig. 13.

From the layout program, the task order of the machines and the positions of all the platforms are sent over to Visual Components. When the data has been transferred, the layout is generated, the simulation is programmed automatically, and the simulation is then executed. If there is a problem when running the simulation, it will be stopped and an error message will be returned. As mentioned in Section 3.3, the robot arm might not be capable of picking up an item at certain angles of the tool center point. Therefore, the simulation serves as a verification tool to determine if the robot arm can pick the item.

In addition, the simulation can be used to:

- Validate if the RMS looks reasonable.
- Check if there is any collision between the platforms.
- Check if there is any collision when the robot arm is working.

If one of the tests fails, the simulation sends a message back to the layout program that the solution is not satisfactory. Then, the layout program will send the second-best solution and the simulation is again tested. A flowchart showing how the system work can be seen in Fig. 14.

4.3. Configuration testing

To showcase the layout generation in python, four different manufacturing layouts were tested. The layouts are tested for both optimization with rotation between 0 to 360 degrees and for fixed 0, 90, 180, and 270 degrees rotation. For the generated layouts, 3D printers, work platforms, and conveyors are used. The work platform is modeled as simple tables in the digital model. However, they are meant to represent manufacturing processes such as CNC machining, coordinate-measuring machine, assembly or other manufacturing processes.

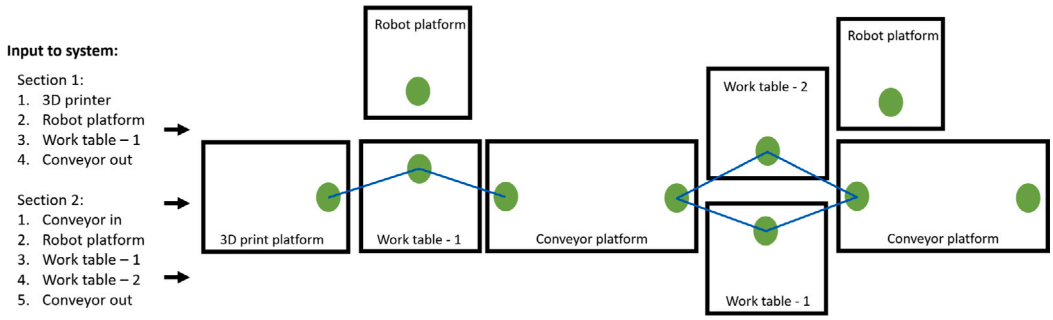

Fig. 12. The input to the optimization model and the system.

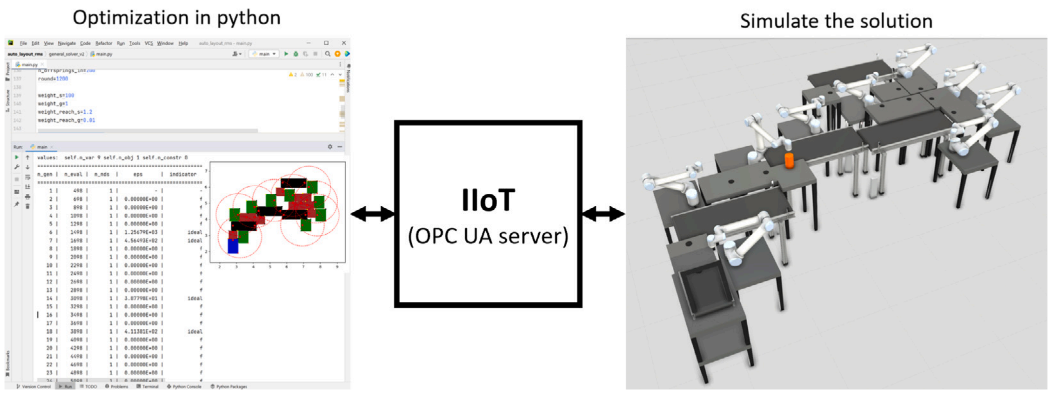

Fig. 13. How the optimization program in python is connected to the simulation software Visual Components.

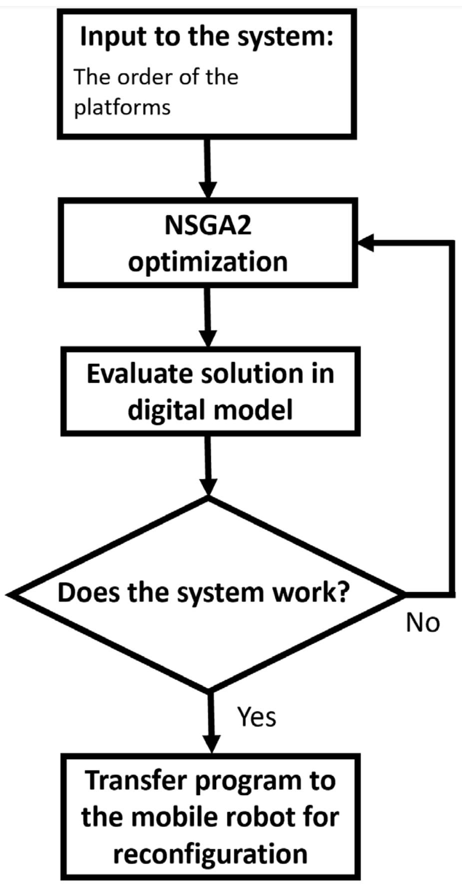

Fig. 14. Flowchart of how the smart layout design system works.

4.3.1. *Layout 1 (three platforms, simplest form)*

The first layout is the simplest form of the system. It includes a 3D printer platform, a robot platform and a conveyor. The results from the optimization can be seen in Fig. 15. A video of the simulation can be found at https://youtu.be/YVbpl2U_L8I.

4.3.2. *Layout 2 (seven platforms in one line)*

The second layout has one section with two 3D printers as input, two work platforms in parallel, two robot platforms and a conveyor. The result from the optimization can be seen in Fig. 16 and a video of the simulation in https://youtu.be/MTCSDvy0Qag.

4.3.3. *Layout 3 (two sections)*

There are two sections for the third layout. In this case, the conveyor is used as a bridge between the two sections. The idea of this layout is to showcase how parallel systems can be connected to create larger manufacturing layouts. The results are shown in Fig. 17, and a video demonstration can be found at https://youtu.be/gZxg1X57g3Y.

4.3.4. *Layout 4 (big system)*

The last layout consists of four sections with different amounts of platforms in each section. This is to test the optimization on a large system and see how much time it takes to solve the problem. Fig. 18 shows the results from the optimization and a video can be found at https://youtu.be/GFiIdPl_0_E.

Table 1 provides details on the optimization time and the number of generations necessary to produce the generated layouts.

4.4. *Test on a physical system*

To test and validate the layout, the system is tested on a physical RMS. The RMS consists of five platforms:

- Robot arm 1 (Nachi MZ07)
- Robot arm 2 (Scara Adept 604)

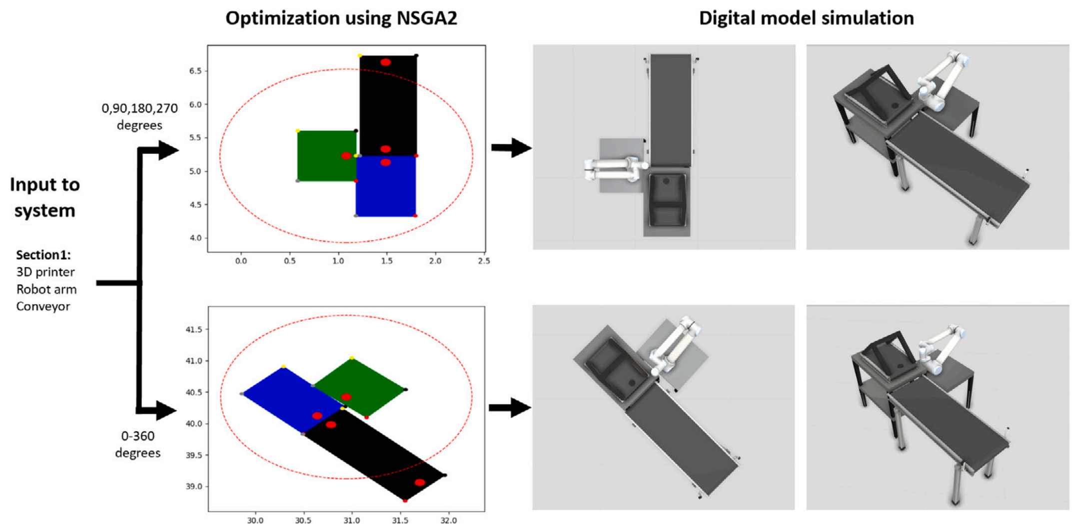

Fig. 15. The result after running optimization for layout one. On the left side is the input to the Pymoo optimizer, in the middle is the result from the optimization, and on the right side is the simulation.

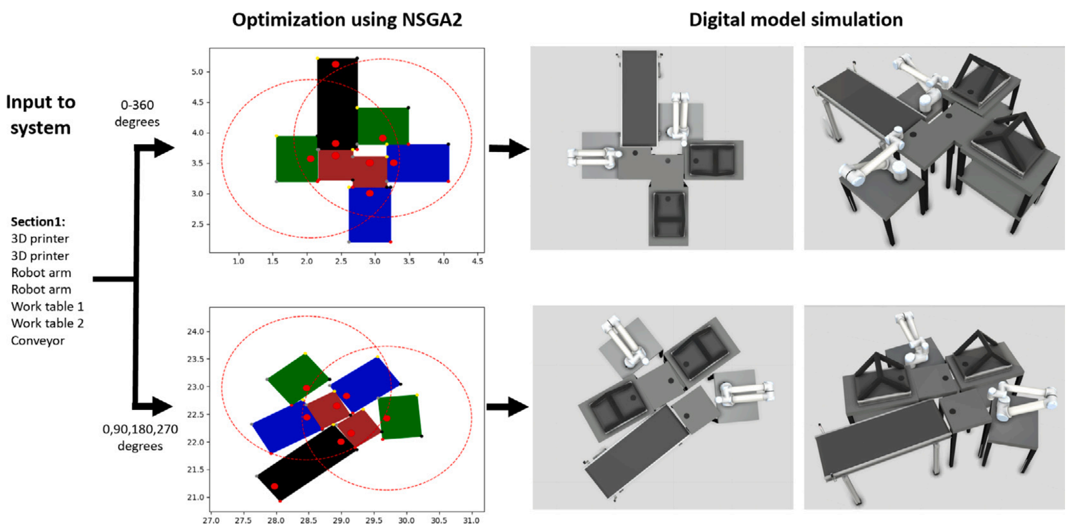

Fig. 16. The result after running optimization for layout two. On the left side is the input to the Pymoo optimizer, in the middle is the result from the optimization, and on the right side is the simulation.

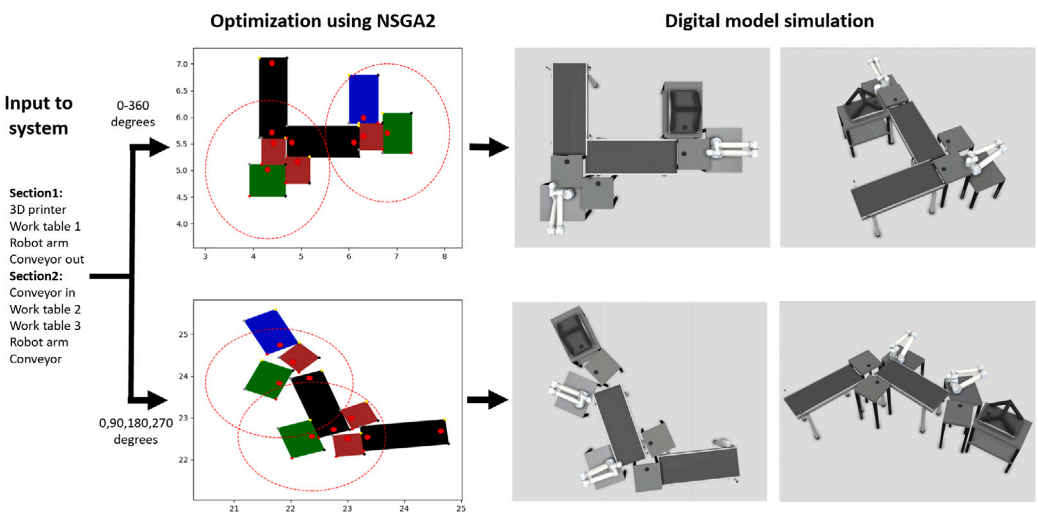

Fig. 17. The result after running optimization for layout three. On the left side is the input to the Pymoo optimizer, in the middle is the result from the optimization, and on the right side is the simulation.

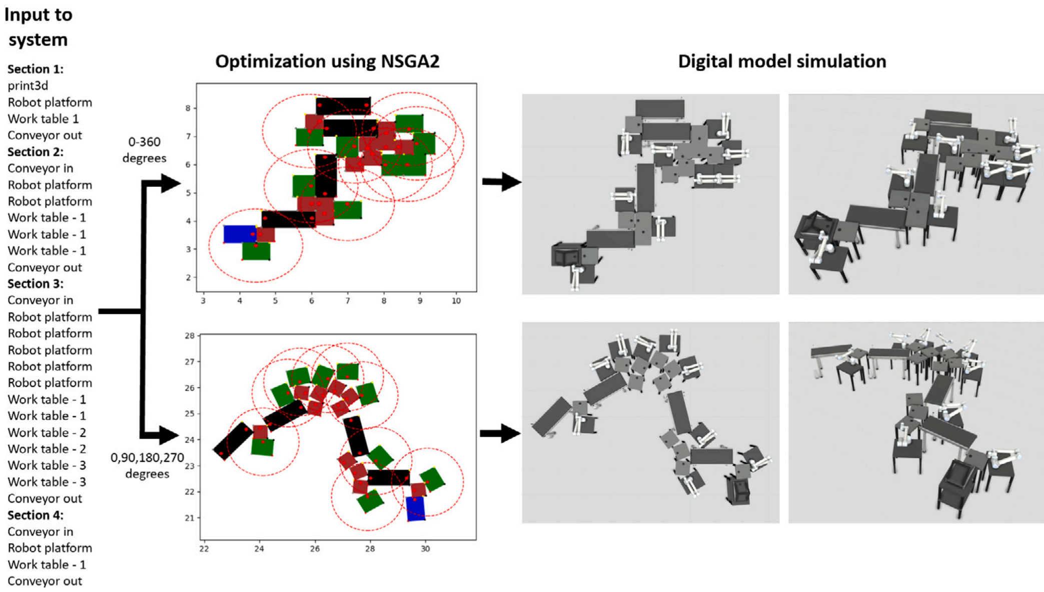

Fig. 18. The result after running optimization for layout four. On the left side is the input to the Pymoo optimizer, in the middle is the result from the optimization, and on the right side is the simulation.

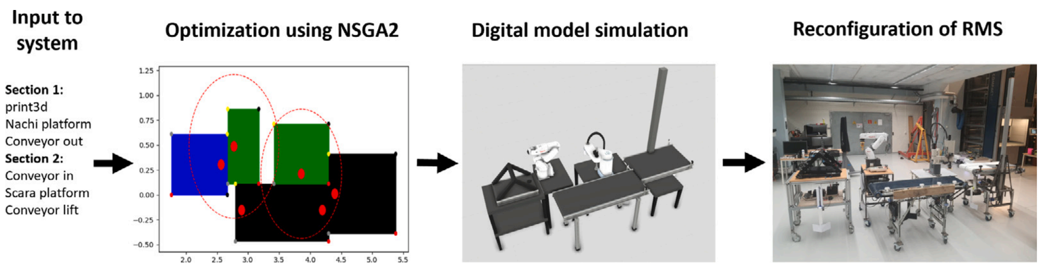

Fig. 19. Illustration of how the system works. On the left side, the input to the optimization, then the resulting layout from optimization, which is transferred over to the simulation/digital model, and on the right side the layout on the physical RMS.

Table 1
The table shows the optimization time, for the layouts tested.

	Rotation	Optimization time (min)	Generations	Number of platforms
Layout 1:	0–360	0.88	393	3
Layout 1:	0, 90, 180, 270	0.72	325	3
Layout 2:	0–360	25.66	1400	7
Layout 2:	0, 90, 180, 270	12.72	750	7
Layout 3:	0–360	77.75	3985	8
Layout 3:	0, 90, 180, 270	17.99	800	8
Layout 4:	0–360	1838.49	8380	25
Layout 4:	0, 90, 180, 270	898.95	2685	25

- 3D print platform
- Conveyor platform
- Conveyor with lifting platform

These platforms can be moved and rearranged automatically by the use of a mobile robot. The mobile robot is equipped with a docking module on top, which allows it to fasten itself to the platform, and can pull the platform. The system is controlled through the OPC UA standard and it is therefore possible to connect the optimization and digital model simulation in Visual Components directly to the physical system. An illustration of the connection can be seen in Fig. 19.

When testing the layout of the physical system, it was shown that it is not feasible to have the platforms too close to each other. This is due to the mobile robots' low accuracy when reconfiguring the platform. To solve this issue, all platforms receive a safety distance between each other, which equals 200 mm.

A video demonstrating the system can be found at https://youtu.be/TqimTSBvpTs. In the video, a layout is generated with NSGA2 optimization, tested with the digital model simulation, and then sent to the physical system for automatic reconfiguration with the mobile robot.

5. Discussion

The idea of RMS is to have a manufacturing system that can rapidly be changed depending on what is being manufactured. However, designing and reconfiguring such a system is both time-consuming and costly due to the requirement of excessive human labor. In this paper, we propose a new approach to automize the reconfiguration process of RMS. We combine optimization with industry 4.0 technologies, i.e., IIoT, digital model, simulation, and advanced robotics to create a smart layout design system for RMS.

We first formulate a mathematical model for a platform-based RMS proposed by Arnarson [10]. The mathematical model for the system is used to yield a score for the system, where penalties are added to the score if certain criteria are not met. The main goal of the system is to reduce the distance between the points of the platforms while all movement platforms can reach the points. This model is then used with an NSGA2 optimizer to find a near-optimal layout. The model can be used for manufacturing platforms of different shapes, and different constraints can be added depending on the requirements of the platforms. Constraints and platforms can easily be changed, and the system can consider other optimization requirements or constraints.

Only using the mathematical model for optimization can be limited, and it can be time-consuming to model all constraints. Therefore, adding a digital model and simulation helps test the manufacturing system. It can be used as a verification tool to validate if the solution from the optimization work in a simulation environment. In addition, connecting the optimization model to the simulation can allow for bi-directional communication between both systems. As a result, the simulation software can provide a quality check and safeguard on the optimization program's solution.

In this project, we tested different rotations for the platforms. One with fixed 0, 90, 180, and 270 degrees and one which is between 0 to 360 degrees. As can be seen from the four layouts (Figs. 15–18), when 0–360 degrees is used, the optimization function will not converge and will therefore not give an optimal layout. By limiting the rotation to 0, 90, 180, and 270 degrees, an improved solution is obtained compared to using 0 to 360 degrees. Having the rotation between 0–360 degrees adds more complexity and possibilities to the system and from the optimization, it looks like the NSGA2 gets stuck. This may be due to the hyper-parameters for the NSGA2 are not exploratory enough.

We have demonstrated four different cases of how the system works and tested the layout optimization on a physical system. In the physical test, we connected the optimization, digital model/simulation and the physical system by using an IIoT (OPC UA) server. Being able to connect the optimization model and digital model directly to a physical RMS allows for increased automation. On the other hand, manually designing the same system would require a human operator with expertise in manufacturing to design the layout. Simulating the system would also require programming, which is time-consuming. The proposed system automates the optimization of the layout, virtually test the layout with simulation, and reconfigure a system with a mobile robot allowing for full reconfiguration without any human intervention. However, the system may not be able to provide the shortest moving path for the workpieces and the most effective use of the RMS modules. Therefore, this system can work as a support tool to help the human operator quickly design and adjust the RMS layout for customized orders, which forms the foundation of the future human–machine interaction in a collaborative manufacturing environment. This system is well-suited for manufacturing systems that undergo frequent process reconfiguration, such as companies operating within industries characterized by high product variety and short product lifecycles, e.g., electronics manufacturing or manufacturing of customized products. Implementing a smart layout design system can greatly benefit manufacturing companies specializing in mass customization or mass personalization by streamlining and reducing the time required for planning and executing new production runs.

As shown in 18, the layout is chaotic and can be considered as not acceptable from a safety and industrial standards perspective. This dilemma is most likely caused by the unrestricted use of platforms to minimize the total movement distance while simultaneously ensuring the reach to all points. A possible solution would be to let the optimization system determine how many platforms are needed, thereby removing unnecessary platforms. Besides, another objective function may also be added to minimize the use of platforms so that the resource requirement could be reduced. Moreover, safety rules and industrial standards can be added to the mathematical model to get a more realistic system.

6. Conclusion

In this paper, we proposed a novel method on how to solve the layout design problem for RMS. We used optimization together with the industry 4.0 technologies, i.e., IIoT, digital model, simulation, and advanced robotics to create a smart layout design for RMS. First, we propose a new mathematical model for the layout design of a platform-based RMS. The object of the mathematical model is to find a layout that minimizes the distance the product has to move while considering the constraints of the system. Then, the NSGA2 algorithm is used to search for an optimal or near optimal layout for the system. The layout is transferred to a digital model simulation software for testing and verification of the system in a virtual space. To showcase how the system works, four different demonstrations were created. The results showed that the mathematical model works and using NSGA2 for optimization can generate a layout automatically and be tested in the digital model. In addition, we also connect the optimization and digital model to a physical RMS to validate the proposed system.

6.1. Future works

6.1.1. Solve the optimization with 0–360 degrees

As mentioned in the discussion, when 0–360 degrees rotation is used, the system will not converge into a good layout. For further work, there should be done an investigation on how to make the system converge. In addition, when the system includes a lot of platforms, it can take a few days for the system to solve the problem. There should also be an investigation into how to improve the computational efficiency of the optimization problem.

6.1.2. Combine optimizations

There has been a lot of work on optimization for process planning, in what order the machines should be in, how many machines are required, how often the system should be reconfigured, and what is the best approach to reconfiguring the system. For further work, these optimization models should be combined together in one system to better model a close-to real-world manufacturing system. For example, when multiple RMSs are set up for different products, some platforms may need to be shared by different RMSs, so not only the positions of the platforms but also the timing for their use needs to be optimized.

6.1.3. Add more objectives and constraints to the system

More and different objectives and constraints can be added to the mathematical model in order to create a more realistic solution. For instance, in this paper, we assume that all parts move from one single point on the platforms. Therefore, adding a constraint that considers an area where parts can be placed would be more realistic and should be added to the optimization. Furthermore, adding another objective to minimize the use of platforms while simultaneously ensuring an acceptable level of reach to all points may help to solve the problem shown in Fig. 18. Moreover, the model can be developed in a 3D space and also take into consideration the limitations in the orientation of the robot arms' tool center point (yaw, pitch, and roll).

6.1.4. General manufacturing systems

Use the same methods in this project to find the optimal layout of a general manufacturing system can be created. As manufacturing systems are usually divided into cells, the position of the machines, walking areas, where the robot should be placed and the different stations can be used to create the most optimal layout depending on the criteria of the model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Koren Y, Heisel U, Jovane F, Moriwaki T, Pritschow G, Ulsoy G, Van Brussel H. Reconfigurable manufacturing systems. CIRP Ann 1999;48(2):527–40. http://dx.doi.org/10.1016/S0007-8506(07)63232-6, URL https://www.sciencedirect.com/science/article/pii/S0007850607632326.

[2] Koren Y, Shpitalni M. Design of reconfigurable manufacturing systems. J Manuf Syst 2010;29(4):130–41. http://dx.doi.org/10.1016/j.jmsy.2011.01.001, URL https://www.sciencedirect.com/science/article/pii/S0278612511000021.

[3] Rösiö C, Bruch J. Exploring the design process of reconfigurable industrial production systems: Activities, challenges, and tactics. J Manuf Technol Manage 2017;29(1):85–103. http://dx.doi.org/10.1108/JMTM-06-2016-0090.

[4] Maganha I, Silva C. A theoretical background for the reconfigurable layout problem. Procedia Manuf 2017;11:2025–33. http://dx.doi.org/10.1016/j.promfg.2017.07.354, URL https://www.sciencedirect.com/science/article/pii/S2351978917305620. 27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017, 27-30 June 2017, Modena, Italy.

[5] Sabioni R, Daaboul J, Le Duigou J. Optimization of reconfigurable manufacturing systems configuration: a literature review. 2020.

[6] Maganha I, Silva C, Ferreira LMDF. The layout design in reconfigurable manufacturing systems: a literature review. Int J Adv Manuf Technol 2019;105. http://dx.doi.org/10.1007/s00170-019-04190-3.

[7] Singh A, Gupta P, Asjad M. Reconfigurable manufacturing system (RMS): Accelerate towards industries 4.0. SSRN Electron J 2019. http://dx.doi.org/10.2139/ssrn.3354485.

[8] Bortolini M, Galizia FG, Mora C. Reconfigurable manufacturing systems: Literature review and research trend. J Manuf Syst 2018;49:93–106. http://dx.doi.org/10.1016/j.jmsy.2018.09.005, URL https://www.sciencedirect.com/science/article/pii/S0278612518303650.

[9] Morgan J, Halton M, Qiao Y, Breslin JG. Industry 4.0 smart reconfigurable manufacturing machines. J Manuf Syst 2021;59:481–506. http://dx.doi.org/10.1016/j.jmsy.2021.03.001, URL https://www.sciencedirect.com/science/article/pii/S027861252100056X.

[10] Arnarson H, Mahdi H, Solvang B, Bremdal BA. Towards automatic configuration and programming of a manufacturing cell. J Manuf Syst 2022;64:225–35. http://dx.doi.org/10.1016/j.jmsy.2022.06.005, URL https://www.sciencedirect.com/science/article/pii/S0278612522001005.

[11] Al-Sahaf H, Bi Y, Chen Q, Lensen A, Mei Y, Sun Y, Tran B, Xue B, Zhang M. A survey on evolutionary machine learning. J R Soc New Zealand 2019;49(2):205–28. http://dx.doi.org/10.1080/03036758.2019.1609052, arXiv:https://doi.org/10.1080/03036758.2019.1609052.

[12] Yelles-Chaouche AR, Gurevsky E, Brahimi N, Dolgui A. Reconfigurable manufacturing systems from an optimisation perspective: a focused review of literature. Int J Prod Res 2021;59(21):6400–18. http://dx.doi.org/10.1080/00207543.2020.1813913, arXiv:https://doi.org/10.1080/00207543.2020.1813913.

[13] Mariem B, Marc Z, AFFONSO R, Masmoudi F, Haddar M. A methodology for solving facility layout problem considering barriers – genetic algorithm coupled with A* search. J Intell Manuf 2020;31. http://dx.doi.org/10.1007/s10845-019-01468-x.

[14] Lim ZY, Ponnambalam S, Izui K. Multi-objective hybrid algorithms for layout optimization in multi-robot cellular manufacturing systems. Knowl-Based Syst 2017;120:87–98. http://dx.doi.org/10.1016/j.knosys.2016.12.026, URL https://www.sciencedirect.com/science/article/pii/S0950705116305317.

[15] Guo H, Zhu Y, Zhang Y, Ren Y, Chen M, Zhang R. A digital twin-based layout optimization method for discrete manufacturing workshop. Int J Adv Manuf Technol 2021;112(5–6):1307–18. http://dx.doi.org/10.1007/s00170-020-06568-0.

[16] Al-Zubaidi SQD, Fantoni G, Failli F. Analysis of drivers for solving facility layout problems: A literature review. J Ind Inf Integr 2021;21:100187. http://dx.doi.org/10.1016/j.jii.2020.100187, URL https://www.sciencedirect.com/science/article/pii/S2452414X20300625.

[17] Azab A, ElMaraghy H. Mathematical modeling for reconfigurable process planning. CIRP Ann 2007;56(1):467–72. http://dx.doi.org/10.1016/j.cirp.2007.05.112, URL https://www.sciencedirect.com/science/article/pii/S0007850607001138.

[18] Chaube A, Benyoucef L, Tiwari M. An adapted NSGA-2 algorithm based dynamic process plan generation for a reconfigurable manufacturing system. J Intell Manuf 2010;23:1–15. http://dx.doi.org/10.1007/s10845-010-0453-9.

[19] Abderrahmane B, Dahane M, Benyoucef L. A new heuristic for integrated process planning and scheduling in reconfigurable manufacturing systems. Int J Prod Res 2014;52:3583–94. http://dx.doi.org/10.1080/00207543.2013.878056.

[20] Wang W, Koren Y. Scalability planning for reconfigurable manufacturing systems. J Manuf Syst 2012;31(2):83–91. http://dx.doi.org/10.1016/j.jmsy.2011.11.001, URL https://www.sciencedirect.com/science/article/pii/S0278612511000999.

[21] Saxena LK, Jain PK. A model and optimisation approach for reconfigurable manufacturing system configuration design. Int J Prod Res 2012;50(12):3359–81. http://dx.doi.org/10.1080/00207543.2011.578161, arXiv:https://doi.org/10.1080/00207543.2011.578161.

[22] Bensmaine A, Dahane M, Benyoucef L. A non-dominated sorting genetic algorithm based approach for optimal machines selection in reconfigurable manufacturing environment. Comput Ind Eng 2013;66(3):519–24. http://dx.doi.org/10.1016/j.cie.2012.09.008, URL https://www.sciencedirect.com/science/article/pii/S0360835212002240. Special Issue: The International Conferences on Computers and Industrial Engineering (ICC&IEs) - series 41.

[23] Moghaddam SK, Houshmand M, Valilai OF. Configuration design in scalable reconfigurable manufacturing systems (RMS); a case of single-product flow line (SPFL). Int J Prod Res 2018;56(11):3932–54. http://dx.doi.org/10.1080/00207543.2017.1412531, arXiv:https://doi.org/10.1080/00207543.2017.1412531.

[24] Moghaddam SK, Houshmand M, Saitou K, Valilai OF. Configuration design of scalable reconfigurable manufacturing systems for part family. Int J Prod Res 2020;58(10):2974–96. http://dx.doi.org/10.1080/00207543.2019.1620365, arXiv:https://doi.org/10.1080/00207543.2019.1620365.

[25] Guan X, Dai X, Qiu B, Li J. A revised electromagnetism-like mechanism for layout design of reconfigurable manufacturing system. Comput Ind Eng 2012;63(1):98–108. http://dx.doi.org/10.1016/j.cie.2012.01.016, URL https://www.sciencedirect.com/science/article/pii/S0360835212000289.

[26] Benderbal HH, Dahane M, Benyoucef L. Exhaustive search based heuristic for solving machine layout problem in reconfigurable manufacturing system design. IFAC-PapersOnLine 2018;51(11):78–83. http://dx.doi.org/10.1016/j.ifacol.2018.08.238, URL https://www.sciencedirect.com/science/article/pii/S2405896318313624. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[27] Haddou Benderbal H, Benyoucef L. Machine layout design problem under product family evolution in reconfigurable manufacturing environment: A two-phase based-AMOSA approach. Int J Adv Manuf Technol 2019;104. http://dx.doi.org/10.1007/s00170-019-03865-1.

[28] Besbes M, Mahjoub YI, Bonte T, Berger T, Sallez Y, Zolghadri M. Solving facility layout problem with safety consideration of reconfigurable manufacturing and assembly systems. Procedia CIRP 2021;104:1942–7. http://dx.doi.org/10.1016/j.procir.2021.11.328, URL https://www.sciencedirect.com/science/article/pii/S2212827121012269. 54th CIRP CMS 2021 - Towards Digitalized Manufacturing 4.0.

[29] Yamada Y. Dynamic reconfiguration of reconfigurable manufacturing systems using particle swarm optimization. In: Proceedings 2006 IEEE international conference on robotics and automation, 2006. ICRA 2006. 2006, p. 1444–9. http://dx.doi.org/10.1109/ROBOT.2006.1641912.

[30] Zheng L, Zhu L, Wang B, Bai L. A simulation analysis of facility layout problems in reconfigurable manufacturing systems. In: 2013 international conference on computer sciences and applications. 2013, p. 423–7. http://dx.doi.org/10.1109/CSA.2013.106.

[31] Petroodi SEH, Eynaud ABD, Klement N, Tavakkoli-Moghaddam R. Simulation-based optimization approach with scenario-based product sequence in a reconfigurable manufacturing system (RMS): A case study. IFAC-PapersOnLine 2019;52(13):2638–43. http://dx.doi.org/10.1016/j.ifacol.2019.11.605, URL https://www.sciencedirect.com/science/article/pii/S2405896319315927. 9th IFAC Conference on Manufacturing Modelling, Management and Control MIM 2019.

[32] Santos R, Toscano C, de Sousa JP. A new simulation-based approach in the design of manufacturing systems and real-time decision making. IFAC-PapersOnLine 2021;54(1):282–7. http://dx.doi.org/10.1016/j.ifacol.2021.08.033, URL https://www.sciencedirect.com/science/article/pii/S2405896321007424. 17th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2021.

[33] Touckia JK, Hamani N, Kermad L. Digital twin framework for reconfigurable manufacturing systems (RMSs): design and simulation. Int J Adv Manuf Technol 2022;120(7–8):5431–50. http://dx.doi.org/10.1007/s00170-022-09118-y.

[34] Leng J, Liu Q, Ye S, Jing J, Wang Y, Zhang C, Zhang D, Chen X. Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model. Robot Comput-Integr Manuf 2020;63:101895. http://dx.doi.org/10.1016/j.rcim.2019.101895, URL https://www.sciencedirect.com/science/article/pii/S073658451930167X.

[35] Kurniadi KA, Lee S, Ryu K. Digital twin approach for solving reconfiguration planning problems in RMS. In: Moon I, Lee GM, Park J, Kiritsis D, von Cieminski G, editors. Advances in production management systems. Smart manufacturing for industry 4.0. Cham: Springer International Publishing; 2018, p. 327–34.

[36] Hajjem E, Benderbal HH, Hamani N, Dolgui A. Digital twin framework for reconfigurable manufacturing systems: Challenges and requirements. In: Dolgui A, Bernard A, Lemoine D, VonCieminski G, Romero D, editors. Advances in production management systems: artificial intelligence for sustainable and resilient production systems, APMS 2021, PT II. IFIP advances in information and communication technology, vol. 631, IFIP Working Grp 5 7 Advances Prod Management Syst; IMT Atlantique, Campus Nantes; Centrale Nantes; Univ Nantes; Rennes Business Sch; Audecia Business Sch; 2021, p. 553–62. http://dx.doi.org/10.1007/978-3-030-85902-2_59, IFIP WG 5.7 International Conference on Advances in Production Management Systems (APMS), Nantes, FRANCE, SEP 05-09, 2021.

[37] Deb K, Pratap A, Agarwal S, Meyarivan T. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 2002;6(2):182–97. http://dx.doi.org/10.1109/4235.996017.

[38] Bensmaine A, Dahane M, Benyoucef L. Simulation-based NSGA-II approach for multi-unit process plans generation in reconfigurable manufacturing system. In: ETFA2011. 2011, p. 1–8. http://dx.doi.org/10.1109/ETFA.2011.6059047.

[39] Verma S, Pant M, Snasel V. A comprehensive review on NSGA-II for multi-objective combinatorial optimization problems. IEEE Access 2021;9:57757–91. http://dx.doi.org/10.1109/ACCESS.2021.3070634.

[40] Yusoff Y, Ngadiman MS, Zain AM. Overview of NSGA-II for optimizing machining process parameters. Procedia Eng 2011;15:3978–83. http://dx.doi.org/10.1016/j.proeng.2011.08.745, URL https://www.sciencedirect.com/science/article/pii/S1877705811022466. CEIS 2011.

[41] Blank J, Deb K. pymoo: Multi-objective optimization in python. IEEE Access 2020;8:89497–509.

[42] Visual Components. 2022, URL https://www.visualcomponents.com. [Online; accessed 10. Sep. 2022].

[43] Munirathinam S. Chapter six - industry 4.0: Industrial internet of things (IIOT). In: Raj P, Evangeline P, editors. The digital twin paradigm for smarter systems and environments: the industry use cases. Advances in computers, vol. 117, Elsevier; 2020, p. 129–64. http://dx.doi.org/10.1016/bs.adcom.2019.10.010, URL https://www.sciencedirect.com/science/article/pii/S0065245819300634.

[44] Foundation O. Unified architecture. 2022, URL https://opcfoundation.org/about/opc-technologies/opc-ua/. [Online; accessed 10. Sep. 2022].

Paper 8

Intelligent and self- reconfigurable manufacturing system

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Halldor Arnarson has contributed substantially in the proposal of research idea, concept, literature review, graphics produce, programming, experimental analysis and writing of the paper.

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Intelligent and self- reconfigurable manufacturing system

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Abstract

Customer demand and profit potential have pushed companies to offer diverse customization options in their products and move towards mass customization. To move towards mass customization reconfigurable manufacturing systems (RMS) have been prosed as a solution. However, it comes with challenges, including labor, costs, time, and complexity. Introducing intelligence, smartness and state-of-the-art industry 4.0 technologies into reconfigurable manufacturing systems (RMS) can be a solution to these challenges. Combining these concepts can be used to develop an intelligent RMS that can be automatically reconfigured without any human intervention. In this paper, a novel architecture has been proposed that explains all the details from the idealization phase to design and physical implementation. The architecture covers individual elements of the RMS, introduces the technologies that enable intelligence and follows through the steps that add up to the complete functionality of the system. In addition, we propose an intelligent process that automates the reconfiguration phase of our proposal. Based on this architecture and intelligent reconfiguration, a physical demonstration is also presented that shows how the system can be implemented. The constructed system is demonstrated as an intelligent RMS capable of mass customization without human effort.

Keywords: Reconfigurable manufacturing system (RMS); Industry 4.0; Intelligent control

1. Introduction

With globalization and a more connected world, the competition between manufacturing companies has increased. Realizing the profit potential, manufacturing companies are offering more customizable products than ever before, thus moving away from mass production and focusing on mass customization and personalized production [1].

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Introducing product customization in manufacturing processes comes with a lot of challenges including costs, manufacturing limitations, reconfiguration times, extra labor, and scheduling [2]. To address these challenges, the concept of reconfigurable manufacturing systems (RMS). RMS enables a system to readjust its cyber and physical resources in a resilient, sustainable and adaptable way based on the dynamic needs and sudden changes [3]. The idea of RMS is to have a system that is designed on both the hardware and software levels for undergoing rapid changes. These are dynamic modular systems that can be taken apart and rebuilt into a new manufacturing system thus changing their functionality and manufacturing capacity based on the product specification [4, 5].

However, the field of RMS is still in the early stages of research and development. There are many research questions that need to be addressed and challenges that need to be solved. For example, a major challenge of having a manufacturing system that can be reconfigured quickly is that it adds a lot of complexity to the system [6]. Similarly, after each reconfiguration, the system needs to be reprogrammed. Programming robots, conveyors, and 3D printers to work in harmony require expertise with the manufacturing equipment and is time-consuming, requires human labor and is expensive. Another challenge with RMS is the layout design problem [7, 8]. Frequently planning a new rearrangement for the RMS consumes a lot of effort and resources. Moreover, Maganha et al. [9] analyzed the barriers to implementing an RMS and noted that Industry 4.0 technologies can help companies overcome the barriers.

The fourth industrial revolution introduced state-of-the-art technologies and concepts, which can help manufacturing companies become more competitive and flexible in their production. There is no agreed list of what technologies are included in Industry 4.0, but 10 technologies have been found to be often considered when discussing Industry 4.0. These technologies are the internet of things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), big data and analytics, cloud technology, simulation and modeling, additive manufacturing, virtualization, and advanced robotics [10]. According to Maganha et al. [9], these technologies can together be employed to fulfill the design and construction needs of an RMS.

There is however a lack of research into Industry 4.0 implementation and intelligent manufacturing into RMS. Bortolini et al. [11] did a literature review on the research directions and concluded that there is a need for more research on reconfigurability toward Industry 4.0. Cunha et al. [12] proposed a modular design of digital twins for RMS. They found that RMS and digital twins complement each other and that digital twins are necessary for the effective management of manufacturing systems. Hence, in an RMS with frequent changes, its digital twin must change in synchronization. Cunha et al. also noted that further research should focus on the automation of reconfiguration. Moreover, Singh et al. [13] found that the technologies in Industry 4.0 are vital for the future success of RMS.

Although scarce, there are some examples of Industry 4.0 integration into RMS. Adamietz et al. [14] developed an RMS inside a container, utilizing additive manufacturing due to its ability to produce highly customized parts. Notably, a complete reconfiguration of their system demands as much as eight hours and necessitates human intervention. Arnarson et al. [15] developed an RMS that utilized multiple Industry 4.0 technologies. A mobile robot could reconfigure the system and the reconfiguration takes around 13 min. However, when the system has been reconfigured a new program has to be created for each platform in the system. The authors note that for further work, there is a need to develop a standard method to automatically program/control the RMS.

One method to create a highly automated and self-controlling manufacturing system can be to use smart manufacturing. Smart manufacturing relies on Industry 4.0 technologies. The goal of smart manufacturing is to reduce human labor while increasing automation. To achieve this, AI along with other technologies such as IIoT and CPS can be used for quality control [16]. Combining smart manufacturing with RMS can allow the systems to become more autonomous, self-controlling, and flexible. Zhu et al. [17] noted that RMS is a model for smart manufacturing, where Industry 4.0 technologies such as digital twins are key enablers to enhance smart manufacturing.

There are two terms used to describe the next generation of manufacturing systems: smart and Intelligent manufacturing. Both of these terms are often referring to the same technology and it can be hard to identify the difference between them. Wang et al. [18] did an investigation on the literature on the difference. They found that smart manufacturing is used more with Industry 4.0, big data, and data-driven concepts. While intelligent manufacturing is used more with AI, optimization, agent systems, and architecture. It is also to be noted that smart and intelligent manufacturing are both used with networking, digital technologies, and intelligentization. However, since AI is often considered to be an integral part of Industry 4.0 and it is known that big data and analytics involve AI methods, it can be argued that smart and intelligent manufacturing are the same thing. In this article, we define smart and intelligent manufacturing to be the same concepts.

The literature on the implementation of RMS is still immature and insufficient. Khanna et al. [19] reviewed research on RMS and concluded that implementation still remains a challenge. For further research, they recommend focusing on efficient methods to design RMS and taking a pragmatic approach. Singh et al [20] found that there should be more research on developing simple principles on how reconfigurable machines and systems are created. Morgan et al. [21] in a literature review on smart reconfigurable machines noted that there is a need for further research in architecture for smarter and reconfigurable machines. They emphasized that the architecture should be simple and focused on high-speed automation. In addition, Sahoo et al. [16] found that there is a lack of knowledge regarding the integration of smart manufacturing technologies. They also noted that having a framework for adopting smart manufacturing technologies can make it easier to implement smart manufacturing. To the authors' knowledge, there is no publication of an architecture for intelligent RMS, that demonstrates how such a system can be implemented. In addition, there is a lack of publication that shows how the reconfiguration of an RMS can be automated.

In this paper, a novel architecture for constructing an intelligent RMS is proposed. The architecture formulates the components of an intelligent RMS, detailing their connections and controls. Industry 4.0 technologies are incorporated into the architecture, with robot arms employed as workers. Additionally, a methodology for automating the reconfiguration process without human intervention is introduced, illustrating how robot arms are automatically controlled using image recognition and digital twin. Demonstrations are also provided to illustrate the practical implementation of this architecture and methodology on a physical system.

The organization of the rest of the paper is as follows: In section 2, literature on intelligent/smart manufacturing and RMS is reviewed. Section 3 presents an architecture for intelligent RMS, while section 4 showcases its application to a physical system. Results are discussed in section 5 and conclusions are drawn in section 6.

2. Related work

In more broad research, intelligent or smart manufacturing often utilizes Industry 4.0 technologies. Therefore, we first review the key technologies and their applications for general smart or intelligent manufacturing systems.

One of the most important technologies from Industry 4.0 that is required to move towards intelligent manufacturing is IoT. Chen [22] looked at industrial IoT (IIoT) technologies and how they are used in manufacturing workshops. They created a reference architecture for smart factories and concluded that IIoT is the foundation of smart factories and intelligent manufacturing systems. Tang et al. [23] designed an intelligent production system that used edge decision-making. The system used OPC UA and data distribution service to communicate with the intelligent production edge.

Another technology that is also often considered in intelligent manufacturing is the digital twin. Cheng et al. [24] looked at the connection between IIoT and digital twin. Moreover, they also proposed a framework towards smart manufacturing with IIoT and digital twin. Li et al. [25] developed a small-scale robotic production station that uses intelligent additive manufacturing. A digital twin is developed for the station that can be used to monitor and control the system. Lu et al. [26] investigated the research challenges related to digital twin-driven smart manufacturing. The researchers found that humans use digital twins for monitoring and decision-making. However, the digital twin should also be used with autonomous control of the physical system in a smart manufacturing system.

AI is also considered to be an integral part of intelligent manufacturing. Kim et al. [27] created a smart manufacturing system that uses multi-agents with reinforcement learning. The idea is to have a system with intelligent agents that can make their own decisions, can interact with other systems, and learn from changing environments. The system is not tested in a physical environment. For further work, they suggest looking at how a smart manufacturing system can react to machine failure, cancellation, or rush in ordering. Zhang et al. [28] did a review on deep learning methods for robot vision applications in smart manufacturing. Robot vision can be used for object detection, segmentation, and tracing of objects. They noted that there are challenges when applying robot vision. For example, some image recognition models such as Faster RCNN and CenterNet can achieve very good detection, but it can be difficult to implement them on mobile hardware platforms.

Another AI method that can make manufacturing systems more intelligent is to use convolutional neural network (CNN). A CNN is a feedforward neural network that can extract features from an image using convolution structures [29]. Verana et al. [30] used CNN to develop an intelligent fault diagnosis for 3D printers. The system can detect various faults when the 3D printer is printing. Haghnegahdar et al. [31] proposed a theoretical framework for a cloud-based intelligent additive manufacturing system.

Zhong et al. [32] did a literature review on intelligent manufacturing and important technologies that are linked to intelligent manufacturing such as IoT, big data analytics, CPS, and information and communication technology. For further work, they noted that there is a need for a generic framework for intelligent manufacturing. The idea is to have a general structure to make it easier to implement intelligent manufacturing systems. It should include Industry 4.0 technologies such as wireless communication standards, advanced sensors and big data models and algorithms.

All the papers mentioned above focus on general manufacturing systems. However, in manufacturing, there are different types of manufacturing systems such as dedicated manufacturing systems, flexible manufacturing systems, and RMS [5]. Each of these manufacturing types has different challenges. For example, one of the major challenges with RMS is the reconfiguration of the system. The reconfiguration process for an RMS requires expertise and can be a time-consuming job that also requires human labor. Moreover, [21, 16] also noted and emphasized the need for a smart manufacturing architecture or framework for RMS. Lee et al. [33] proposed an architecture for a decision model of reconfigurable manufacturing systems. The architecture is based on fractal and smart manufacturing concepts. However, there is a lack of examples of how architecture can be linked to a physical system. In addition, it is mentioned that they don't use real data and do not cover all aspects and mechanisms of such systems.

Zhu et al. [17] created a dynamic reconfiguration optimization method for an intelligent manufacturing system that used a digital twin for human-robot collaboration. They looked at a case with one operator, one robot, and one machine tool and concluded that more complex manufacturing scenarios should be looked at. In addition, the system was not tested on a physical RMS. Friederich et al. [34] investigated a data-driven simulation for smart manufacturing systems. The authors noted that to do an Industry 4.0 integration, a digital twin is needed. They also found that performing manual simulation modeling is not possible in today's environment, where manufacturing systems have many fast reconfigurations. Hence, there is a need for a method to create digital twin simulation models of the manufacturing system in an efficient and fast manner. The proposed method can be used to generate data-driven simulations with digital twin data.

From the reviewed literature, most research focuses on implementing one or two Industry 4.0 technologies for intelligent manufacturing systems, with limited work on combining multiple technologies. Practical implementation examples and research on RMS integration with intelligent manufacturing and Industry 4.0 are scarce. Studies on automating the reconfiguration process using Industry 4.0 technologies are also lacking.

3. Architecture for Intelligent RMS

In this chapter, we propose an architecture detailing the components and functionality of an intelligent RMS. This architecture focuses on the machine or manufacturing cell level, excluding connections to high-level systems (e.g., Enterprise Resource Planning (ERP), Material Requirements Planning (MRP), and Customer Relationship Management (CRM)).

Additionally, the architecture is designed based on Arnarson et al.'s highly flexible modular system concept [15], which uses a mobile robot for autonomous reconfiguration. The reconfiguration scheme is product-specific. The architecture's objectives include: Showcasing key elements/platforms/modules and ideal characteristics for an intelligent RMS; Defining tools and methods to enhance intelligence in individual elements and the overall system; Proposing a method for smart communication and data storage within the system; Incorporating optimization and algorithms for automatic programming, control, and layout formation with minimal human effort; Establishing a sequence and hierarchy of RMS steps; Structuring the architecture for easy industry adoption, development, and physical implementation. The following sections describe the aspects, elements, and functionalities included in the architecture based on these criteria.

3.1. Elements of the architecture

An RMS usually includes multiple manufacturing machines and equipment.

It has been observed and deduced that these machines can be broadly generalized into three categories, and most manufacturing processes can be implemented through a combination of them.

The first one is a process platform that performs the main action on a product. Examples of these platforms include 3D printers, CNC machines, turning centers, and cutting machines. For this architecture, a 3D printer has been demonstrated and discussed as the generalized element because of its rising significance as an Industry 4.0 technology. The second platform is a robot arm platform used to autonomously move products between platforms. The third is a conveyor platform that can be considered as the logistical platform in the system to move and store products. Additionally, the architecture consists of two elements to enable supervisory control and data storage in the system. The full architecture of the system can be seen in Fig. 1.

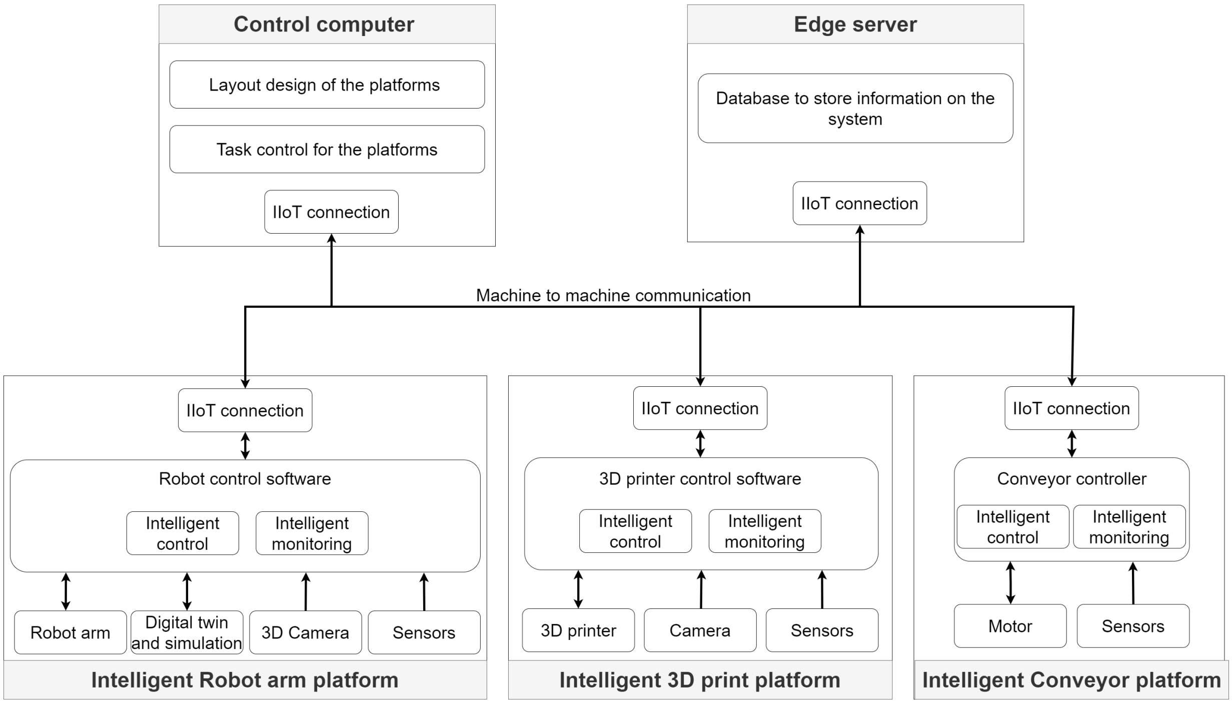

Fig. 1: The architecture for intelligent RMS

Each of these elements/platforms along with the associated Industry 4.0 technologies, tools and methods for introducing intelligence in the RMS are discussed further.

3.1.1. 3D print platform

Additive manufacturing is the most sought-after and optimal manufacturing method because of the direct production and sustainability [35]. In this architecture, a 3D printer is generalized for any platform that performs a process and outputs a part that is ready to be transported forward in the manufacturing line. It is the recommended production platform for this architecture and the further technologies in this paper are discussed with examples of a 3D printer platform.

However, the technologies are equally valid for other process platforms that can contain an assembly station, CNC, or Turning machine. To make the platform intelligent, there is intelligent control and intelligent monitoring. For intelligent control, the 3D printer is connected to an IIoT network for wireless control. The IIoT server can be used by the 3D printing platform to inform the rest of the system when a part is finished printing, and if it was successful or not. In addition, if the system requires a completely new part to be manufactured, the printing management software takes the 3D file, slices it, and generates a G code which can be used to print the part on the 3D printer automatically.

For intelligent monitoring, several methods can be employed to detect how the printing is going and if there is a failure. With 3D printing, there can be a number of failures, such as the nozzle crashing into the printing bed, over and under extruding, and the part falling off the bed while printing. As noted in section 2, CNN can be used together with 3D printer for fault detection. Therefore, a camera is added to monitor the 3D printer while printing. The camera feed is fed into a CNN, to detect different failures. A CNN can be used to detect warping, over and under extrusion, layer separation, stringing, and not sticking to the print bed. If the CNN detects over-extrusion on a part, a message can be sent to the printing management software, and the print will be stopped and thrown away, and a new print can be started, but the extrusion rate is reduced. In the same way, the CNN can also be trained to detect failures through camera feed in other production platforms like CNC and turning machines.

In addition to the CNN, a sensor can be added to the 3D printer that can support the CNN. For example, having a 6-axis velocity and acceleration sensor can help detect if the nozzle is crashing into the printing bed. Using a vibration sensor can monitor if the 3D printer is on a stable surface or is shaking. Machine learning algorithms can also be trained to detect different failures, and these algorithms can be used with CNN to compare and check for failures. In short, a multitude of sensors and cameras need to be used to monitor the production and stop or adjust if a failure is detected.

3.1.2. Robot arm platform

Robot arms are typically designed to perform repetitive tasks with little or no variation. From a review on smart robotics in manufacturing, Liu et al. [36] note that most current robots are programmed manually. However, the next generation of robots should be programmed free and be able to adapt to uncertainties. To make the robot arm platforms intelligent, they need to adapt and see the environment they are working in.

Similar to the 3D printer, the robot control software needs both intelligent- control and monitoring. One method for intelligent control of the robot arm can be to use cameras. Zhang et al. [28] noted in their study that using a 3D vision instead of a 2D vision gives more information on the scene the robot is working in. Using 3D cameras will allow the robot arm to detect the depth and see how far away parts are from the gripper. The images from the 3D cameras are fed into a CNN for image recognition which is able to recognize the part the robot arm will work with. Since image recognition can be used to detect where the part is in an image, it can be used as a navigation tool to control the robot arm automatically and pick parts without any human intervention.

However, one challenge with using image recognition for control is that a specific image recognition model has to be created for each part the robot arm will work with. Traditionally, image recognition models are usually made by first taking a lot of pictures of the parts to be recognized and then manually labeling these images. This process is very time-consuming, dull, and requires human labor.

Another method to create the image recognition model is to use a 3D model to generate the image recognition model. This can be done by first generating images from the 3D model, then feeding these images into a cycle generative adversarial network (GAN) [37] to make the images look more realistic (add shadows and features to make them look like real 3D printed parts). Since the images of the part are in the center, they can be automatically labeled and trained with a CNN. The steps of generating an image recognition model based on a 3D model can be seen in Fig. 2. A detailed explanation of how such a system can be implemented can be found in [38].

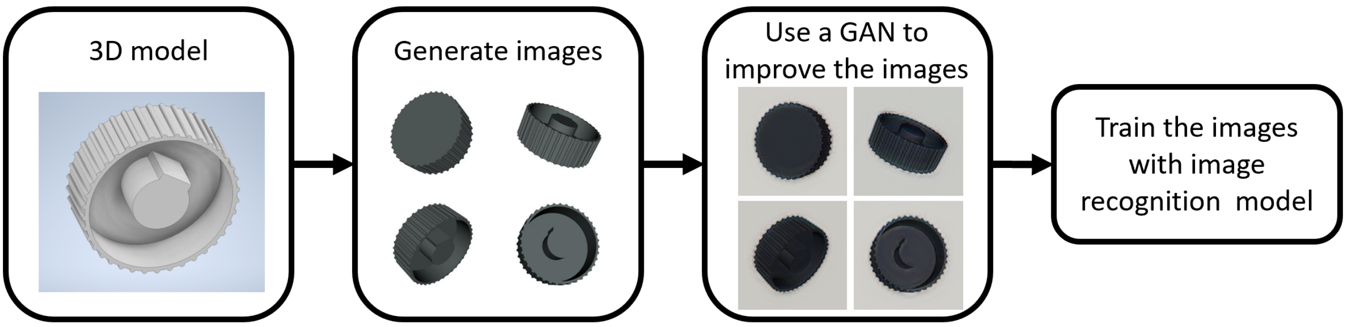

Fig. 2: The figure shows the four steps on how a 3D model can be used to train an image recognition model.

Similar to the 3D printing platform, sensors are also added to the robot arm to detect abnormalities and irregularities when the robot arm is working. For example, acceleration and velocity, or force sensors to detect if the robot arm has crashed. The robot arm platform is also connected to the IIoT server of the system. This is to get the tasks the robot arm should do but also communicate with the other parts in the system.

3.1.3. Conveyor platform

The conveyor platform is the simplest platform. The conveyor platform is used to move parts between robot arms in the manufacturing system. Similar to the 3D printing- and robot arm platform, the conveyor is equipped with sensors to detect abnormalities and to detect where a part is on the conveyor. The conveyor platform is also connected to the IIoT server, where it can be controlled remotely.

3.1.4. Control computer

The control computer is the main controller of the whole system. Although each platform must contain a local computer, the control computer serves as the master of the whole system. Being mobile, the platforms' computers are only powerful enough to perform basic functions. The master computer, on the other hand, should be powerful enough to multitask and run heavy computational operations tasks.

The control computer is responsible for planning and defining tasks from the start of receiving a product order to the complete execution and output. It organizes and commands which tasks the platforms need to perform and generates a new manufacturing layout.

Formation of digital twins and validation is one of the main duties of the control computer. As mentioned earlier, digital twins are another Industry 4.0 technology that has been integrated into this Architecture as a requisite. The reconfiguration, planning and task assignment are decided based on the optimization and information obtained from the digital twin. One important aspect of digital twins in this Architecture is that it enables completely autonomous programming and control of the entire system. Additionally, the control computer should also serve as an interactive human interface for easy communication with an operator and display of information.

3.1.5. Edge Server

An RMS is data savvy and requires methods to organize and maintain the data. In this methodology, an edge server which is an SQL database has been integrated for reliable data storage and access. Each element or platform in the RMS is usually dealing with data, and an edge server enables this flow through an IIoT connection. One important requirement in RMS is to have information on each task of each platform as it helps in troubleshooting and finding faults in the system. Therefore each element in the RMS has read and write access to the database, and the events are continuously logged. It also helps the operator for monitoring the system. In other words, the edge server is responsible for industrial big data tasks. Industrial big data applications can be business Intelligence, product quality enhancement, machine health prediction, fault tolerance, and production planning [39]. In this methodology, the computer collects data from the RMS and uses machine learning algorithms to monitor the system and give status on how the system is performing. In addition, while the RMS is running, data is collected from the sensors, and machine learning algorithms can be automatically updated and trained on new data.

3.2. Intelligent reconfiguration process

After describing the elements of the proposed Architecture, an intelligent reconfiguration process is proposed as an automatic methodology to reconfigure an RMS. In this section, the steps of the process and function are defined and outlined.

The methodology utilizes the RMS proposed by Arnarson et al. [40] and expands it for autonomous, optimal and intelligent performance. Under this proposed methodology, the main purpose of the system is to take a 3D model of a part as an input, autonomously and intelligently perform all the operations and output the desired product. For this purpose, the system goes through a series of steps, each of which is explained in detail further. The process can be divided into six steps, as shown in Fig. 3.

- **Step 1: 3D model** The input to the methodology is a 3D model or assembly file of the part that should be manufactured. Using a 3D model or assembly file, it is possible to extract information and devise a manufacturing plan.
- **Step 2: Required steps/platforms** There has previously been done work on methods that can take information from the 3D models and generate instructions [41, 42]. Thus, it is possible to generate manufacturing instructions automatically. These instructions can further be used to find which platforms are required to manufacture the parts or an RMS operator can also select which platforms to use.

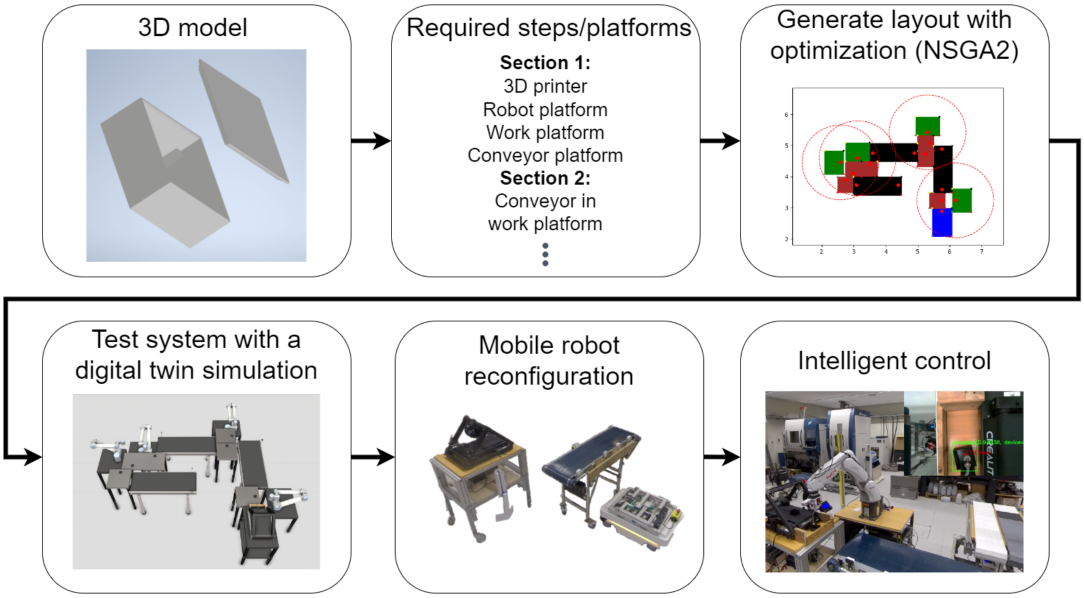

Fig. 3: Six steps of the intelligent layout design.

- **Step 3: Generate layout** Based on the platforms that are required the mathematical model from [40] is employed with evolutionary computation (a subfield of AI) [43]. From evolutionary computation, the non-dominated sorting genetic algorithm 2 (NSGA2) [44], a multi-objective optimization technique, to identify multiple Pareto-optimal solutions. The algorithm optimizes platform coordinates (x, y, θ) for Pareto efficiency, using the required platforms as input.
- **Step 4: Test system with a digital model simulation** After the optimization, platform coordinates are input into a simulation software (Visual Components). With instructions, platform orders, and coordinates of the platforms, we can create a digital model that simulates the manufacturing process. This step checks for collisions and ensures robot arms reach required platforms without colliding with other objects. If errors occur, the simulation communicates with Step 3, requesting an alternative optimization solution.
- **Step 5: Mobile robot reconfiguration** Mobile robots, using simultaneous localization and mapping (SLAM) for navigation can re-plan routes if an obstacle is in the way and are therefore highly flexible and automated. These robots can pick up and move platforms to new locations using provided x, y, θ coordinates. After digital testing, platform coordinates are sent to the mobile robot for reconfiguration.
- **Step 6: Intelligent control** Upon reconfiguration, manufacturing begins with platforms executing tasks assigned by the control computer. The digital twin and instructions facilitate automatic control. Intelligent control integrates AI technologies like CNN, cycle GAN, and machine learning for object detection, failure detection, quality control, and system performance analysis, health, and abnormality detection. Moreover, in the event of a specific failure or abnormality, the system is designed to address the issue or alert the system operator autonomously.

4. Demonstration

A demonstration has been built to showcase how an intelligent RMS works and what parts are in the system. The system proposed in [15, 40] is expanded to create an intelligent self-reconfigurable manufacturing system.

4.1. The intelligent platforms

The system consists of five platforms: a 3D printer, a Nachi (six-axis robot arm), a Scara (four-axis robot arm), a conveyor, and a conveyor lift. These platforms are connected to an OPC UA server for machine-to-machine communication, remote control, and monitoring. Moreover, the server stores the raw sensor data in an SQLite database.

4.1.1. 3D print platform

The 3D printer is used to automatically manufacture parts as they are needed. A CR-30 Creality 3D printer is used and is a conveyor printer that prints with a 45-degree angle. This allows the 3D printer to automatically eject parts from the printer and can print endlessly in the Z direction.

To control and manage the 3D printer, OctoPrint is used. OctoPrint is an open-source software that is most commonly installed on a raspberry pi and can be used to manage, monitor, and control 3D printers connected to it. It can also be used with an API and supports plugins that can add software functionality to the 3D printer. A camera is connected to Octoprint to be able to monitor the 3D printer. Then Obico, which uses image recognition with the camera connected to Octoprint, is employed to do failure detection. Obico is used to warn an operator of the 3D printers or stop the printing and send an email or notification that something has gone wrong. Fig. 4, shows when a print has failed, and the operator has been notified.

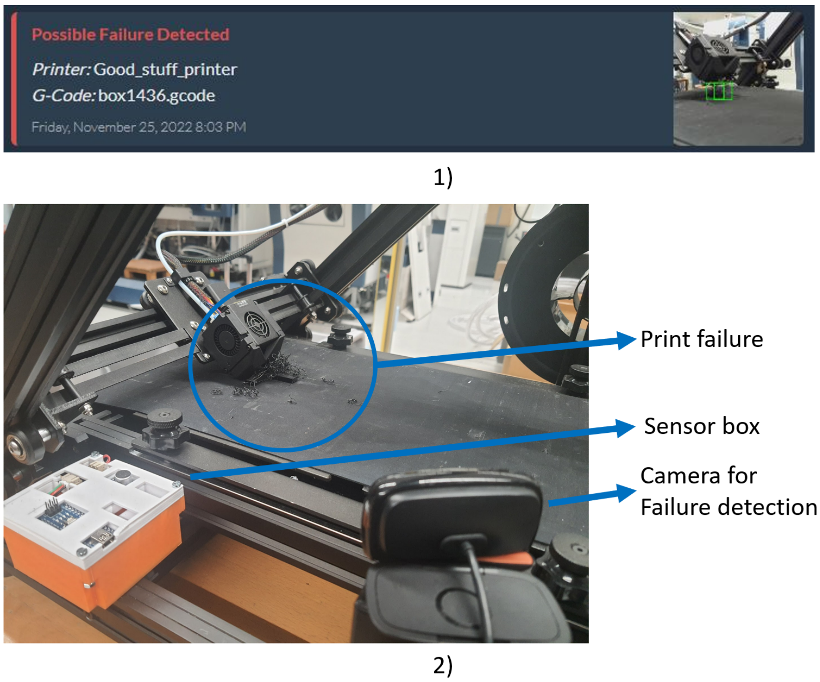

Fig. 4: A example of a 3D print that has failed where Obico has stopped the print and notified the operator.

The failure detection focuses on the part being 3D printed. To be able to detect other faults, such as the nozzle hitting the bed or crashing, a sensor box is added. The sensor box contains a sound sensor, a vibration sensor, a three-axis gyroscope, and an accelerometer. All the data from the sensors is collected and used as additional information to monitor the 3D printer. The data collected from the sensor box and 3D printer can be used with machine learning algorithms to detect abnormalities. The methods proposed in [45] can be used to use the data collected in an RMS.

4.1.2. Robot arm platform

In the system, there are two robot platforms. Both of the robot arms are equipped with the same gripper. The gripper has an intel realsense D405 3D camera, a suction gripper to pick parts, and in the middle of the gripper a sensor box. The 3D camera is used with image recognition to locate and pick up parts automatically. In this system, the 3D camera is used as a navigation tool to control where the robot will move. The sensor box in the gripper is equipped with a sound sensor, a vibration sensor, a three-axis gyroscope, and an accelerometer. It is placed with the gripper because if the robot crashes, it will most likely have the greatest impact on the gripper.

Using the automatic method (described in section 3.1.2) to create image recognition models of 3D models, the robot arms can pick up any object without any human intervention. In the video `https://youtu.be/5w34Q-QYKX8` the robot arm uses the image recognition model which is trained using the 3D model to pick up objects from a conveyor.

4.1.3. Conveyor platform

This system consists of two conveyors. One large conveyor is used to move parts between the robot arms and a second conveyor, can be lifted up and down. As mentioned before, the conveyors are the simplest platforms and have been equipped with a raspberry pi for remote control, ultra sensors to detect the position of the parts, and a sensor box to detect abnormalities.

4.2. Intelligent reconfiguration

Reconfiguring the platforms is the first step in programming an RMS. In this example, a simple box will move through the platforms, and the required platforms are set manually. First, the box is 3D printed, and the Nachi robot arm transfers it to the conveyor platform. The conveyor moves the box, the Scara robot arm relocates it to the conveyor lift, which serves as the final step before the product exits the system.

From these steps, layout optimization is carried out. The generated layout is sent to simulation software to create a digital twin. The solution is tested with digital twin simulation, and platform positions are relayed to the physical RMS for mobile robot-assisted reconfiguration. View a demo at https://youtu.be/SwDNChz57ts. In this example, optimization takes 31.5 minutes using the NSGA2 algorithm, while the mobile robot requires 11.8 minutes to reconfigure the five platforms in the system.

4.3. Automatic programming

A control computer is added to allocate tasks to the different platforms. The instructions from the layout generation are used to define each step in the process. The control computer will therefore send the tasks to platforms, for example, first the 3D printer to print a part, then the Nachi robot will move the part to the conveyor, and so on.

After finishing the layout generation, we have a digital twin of the system. This digital twin is not 100% accurate when it comes to positioning since the accuracy of the mobile robot is rather low. It is therefore not possible to run the simulation program from the digital twin directly on the physical system. However, the digital twin can be used to read the relative distance from the robot arm to the part or the joint rotation of the robot arm, as can be seen in Fig. 5.

This information can be used as a start position for the robot arm. The idea is to use the information from the digital twin to find an estimated position of the part and then start to use the 3D camera for control. For example, at the start, the Nachi robot arm is sent to the position from the digital twin, and then camera vision is used to move the tool center point towards the part. Another approach to finding the object can be to use a grid-based search method. However, the grid-based search method can be slower than using the digital twin to get the start position.

The same system demonstrated from the layout generation is then run automatically on the physical RMS. A demonstration video showing the automatic programming of the platforms can be found at https://youtu.be/Su7A_6GuF0s, and the steps of the demonstration can be seen in Fig. 5. The process involves: 1) 3D printer expelling the part; 2-3) Nachi robot using digital twin coordinates to approach the printer; 4) navigating with a 3D camera to pick up the part; 5-6) positioning it on the conveyor based on the digital twin; 7) conveyor transporting the part; 8-10) Scara robot utilizing digital twin data and 3D camera to place a box on the conveyor lift; 11-14) mobile robot transferring the conveyor lift with boxes for further transport. In this experimental setup, both robot arms and the conveyor operate at a slow pace, taking 3.2 minutes for a box to be transported through the system.

5. Discussion

Both the concept of intelligent manufacturing and RMS complement each other as the manufacturing Industry is moving towards mass customization. Over the last few years, there has been a lot of theoretical work on intelligent manufacturing and RMS, but there is still a lack of research on how to implement such systems. Based on this need, a set of objectives and goals were defined that assisted in developing a functional and applicable architecture. Such an architecture can be a stepping stone for researchers and encourages research on RMS with results based on physical experimentation rather than a theoretical approach. It is also believed that it will promote mass customization in industries in a simpler, cost-effective and labor free way.

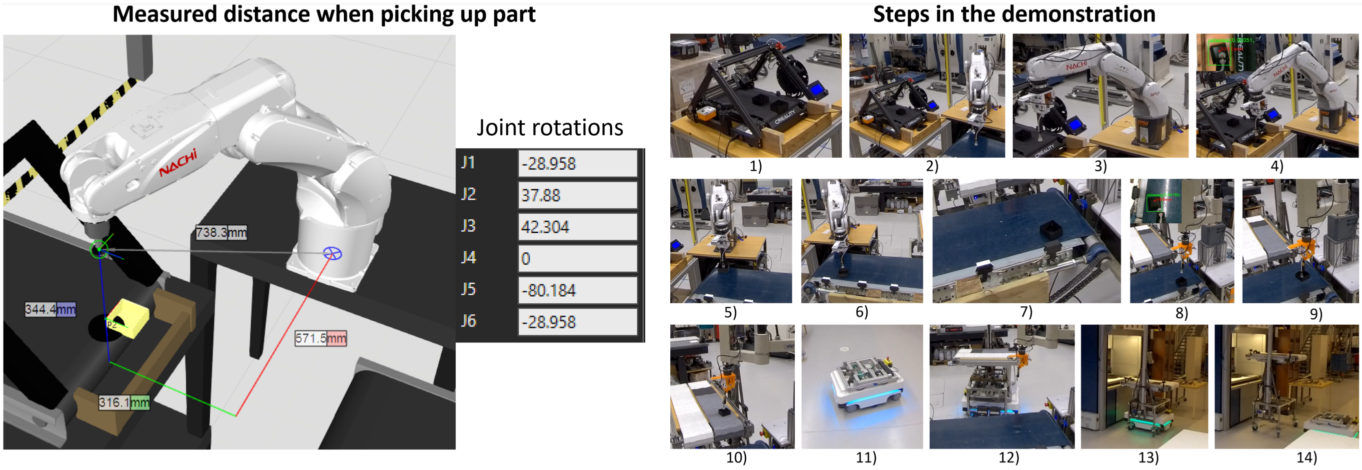

Fig. 5: On the left side, the digital twin displays the relative position and rotation during the process of retrieving a part from the 3D printer. On the right side, the demonstration steps.

The developed architecture for a platform-based RMS enables automatic reconfiguration using mobile robots and incorporates intelligent control and monitoring. Employing various Industry 4.0 technologies such as IoT, digital twins, simulation, big data, analytics, additive manufacturing, advanced robotics, and AI, the system is resilient and capable of corrective measures. AI methods and data processing are extensively used in the architecture, which is designed to be generic and adaptable for various industrial processes, enabling autonomous reconfiguration and intelligence.

The architecture has been developed for a platform-based RMS, where the platforms can be reconfigured automatically using mobile robots. For each of the platforms, there is an intelligent method for control and monitoring. Today, Industry 4.0 technologies are vital for implementing intelligent manufacturing. In the architecture, we utilize multiple Industry 4.0 technologies such as IoT, digital twins, simulation, big data and analytics, additive manufacturing, advanced robotics, and AI. These technologies make the system resilient and able to take corrective measures.Examples of these technologies include video monitoring in process related platforms to autonomously detect failures or incorrections, and sensor boxes to detect abnormalities. Furthermore, most of the architecture's technologies revolve around artificial intelligence. The usage of AI methods and data processing is extensive in this architecture to establish these specifications. Additionally, the architecture has been kept generic and it is claimed that it can be adopted and varied to fit industrial processes, making them autonomously reconfigurable and intelligent.

For better control and system integration, the architecture includes a network of master-slave configurations connected through an IIoT and an edge server. A control computer serves as the master of the whole system. It organizes the whole system, runs optimization and provides independent tasks to each slave platform where the only information forwarded to the platforms is what task to perform. Additionally, a digital twin of the system is introduced. It serves the complete planning phase making certain of error free performance. It also supports the control of the robot arms. From the digital twin, we can read the positions that the robot arms need to move to. By integrating this with a 3D camera for image recognition, an efficient method to control the robot arm is achieved. This method is presented as a faster alternative to a grid-based search system for part identification.

One challenge with RMS is the reconfiguration process which requires expertise and often manual labor. However, the six-step intelligent reconfiguration process is proposed as a method to automate the reconfiguration of RMS. The system takes in a product as a CAD or assembly file and is used as a template to generate the layout for the RMS. Moreover, it is also used to automatically program the robot's arms and other platforms in the system.

Existing RMS and intelligent manufacturing literature lacks physical demonstrations. We've built an RMS showcasing intelligent monitoring and control at both platform and system levels for 3D printer, robot arm, and conveyor platforms. Additionally, automatic layout generation using optimization, digital twin simulation, and mobile robot-assisted automatic reconfiguration is demonstrated, effectively solving the layout design problem for RMS. The optimization time to generate a layout stands at 31.5 minutes indicating a slower process. In contrast, the mobile robot efficiently places the five platforms in 11.8 minutes, demonstrating a faster performance.

The current study possesses several limitations that warrant consideration. Firstly, the demonstration is elementary, illustrated by just two boxes navigating through the system. This setup might not fully capture real-world complexities. Moreover, both robots and conveyors operate at a notably low speed, which could raise questions about the system's efficacy in higher-speed environments.

While the system incorporates specific error-detection mechanisms with the 3D printer and robot arms, there is an evident need for broader research. This exploration should explore diverse methods to utilize sensor data and identify additional data beneficial for the system's enhancement. Moreover, the implications of industrial big data approaches tailored to this system require further investigation. The study's scope, restricted to a plastic 3D printer and certain robot arms, underscores the importance of examining various robots and manufacturing machinery. Further examination is needed to determine how various machines can be designed or reconfigured for wider applicability.

6. Conclusion

In this paper, an architecture for intelligent RMS was proposed. The architecture detailed the different components found within an intelligent RMS and the methods that can be employed to establish the system. Furthermore, multiple Industry 4.0 technologies such as IIoT, digital twin, simulation, industrial big data, AI, and advanced robotics were utilized in the architecture.

Additionally, an intelligent reconfiguration process that automates the reconfiguration procedure of RMS was introduced. This process encompassed six steps, including the rearrangement of the RMS and the identification of a new layout. The robots and other machines within the system were automatically programmed using digital twin, simulation, and AI technologies.

It was also demonstrated how the intelligent RMS architecture and the intelligent reconfiguration process can be utilized to create an intelligent self-RMS. A layout for the system was automatically generated and subsequently reconfigured using a mobile robot in the demonstration. The application of digital twins and image recognition for the automatic control of two industrial robots was also illustrated.

References

[1] M. Fathi, M. Ghobakhloo, Enabling mass customization and manufacturing sustainability in industry 4.0 context: A novel heuristic algorithm for in-plant material supply optimization, Sustainability 12 (16) (2020). doi:10.3390/su12166669.
URL https://www.mdpi.com/2071-1050/12/16/6669

[2] Z. Qin, Y. Lu, Self-organizing manufacturing network: A paradigm towards smart manufacturing in mass personalization, Journal of Manufacturing Systems 60 (2021) 35–47. doi:https://doi.org/10.1016/j.jmsy.2021.04.016.
URL https://www.sciencedirect.com/science/article/pii/S0278612521000960

[3] A. Dolgui, D. Ivanov, B. Sokolov, Reconfigurable supply chain: the x-network, International Journal of Production Research 58 (13) (2020) 4138–4163. arXiv:https://doi.org/10.1080/00207543.2020.1774679, doi:10.1080/00207543.2020.1774679.
URL https://doi.org/10.1080/00207543.2020.1774679

[4] Y. Koren, U. Heisel, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, H. Van Brussel, Reconfigurable manufacturing systems, CIRP Annals 48 (2) (1999) 527–540. doi:https://doi.org/10.1016/S0007-8506(07)63232-6.
URL https://www.sciencedirect.com/science/article/pii/S0007850607632326

[5] Y. Koren, M. Shpitalni, Design of reconfigurable manufacturing systems, Journal of Manufacturing Systems 29 (4) (2010) 130–141. doi:https://doi.org/10.1016/j.jmsy.2011.01.001.
URL https://www.sciencedirect.com/science/article/pii/S0278612511000021

[6] C. Rösiö, J. Bruch, Exploring the design process of reconfigurable industrial production systems: Activities, challenges, and tactics, Journal of Manufacturing Technology Management 29 (1) (2017) 85–103. doi:10.1108/JMTM-06-2016-0090.

[7] I. Maganha, C. Silva, L. M. D. F. Ferreira, The layout design in reconfigurable manufacturing systems: a literature review, INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY 105 (1-4) (2019) 683–700. doi:10.1007/s00170-019-04190-3.

[8] H. H. Benderbal, M. Dahane, L. Benyoucef, Exhaustive search based heuristic for solving machine layout problem in reconfigurable manufacturing system design, IFAC-PapersOnLine 51 (11) (2018) 78–83, 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018. doi:https://doi.org/10.1016/j.ifacol.2018.08.238.
URL https://www.sciencedirect.com/science/article/pii/S2405896318313624

[9] I. Maganha, A.-L. Andersen, C. Silva, L. M. D. F. Ferreira, A classification of the barriers in the implementation process of reconfigurability, in: A.-L. Andersen, R. Andersen, T. D. Brunoe, M. S. S. Larsen, K. Nielsen, A. Napoleone, S. Kjeldgaard (Eds.), Towards Sustainable Customization: Bridging Smart Products and Manufacturing Systems, Springer International Publishing, Cham, 2022, pp. 88–95.

[10] T. Zheng, M. Ardolino, A. Bacchetti, M. Perona, The applications of industry 4.0 technologies in manufacturing context: a systematic literature review, International Journal of Production Research 59 (6) (2021) 1922–1954. arXiv:https://doi.org/10.1080/00207543.2020.1824085, doi:10.1080/00207543.2020.1824085.
URL https://doi.org/10.1080/00207543.2020.1824085

[11] M. Bortolini, F. G. Galizia, C. Mora, Reconfigurable manufacturing systems: Literature review and research trend, Journal of Manufacturing Systems 49 (2018) 93–106. doi:https://doi.org/10.1016/j.jmsy.2018.09.005.
URL https://www.sciencedirect.com/science/article/pii/S0278612518303650

[12] C. da Cunha, O. Cardin, G. Gallot, J. Viaud, Designing the digital twins of reconfigurable manufacturing systems: application on a smart factory, IFAC-PapersOnLine 54 (1) (2021) 874–879, 17th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2021. doi:https://doi.org/10.1016/j.ifacol.2021.08.103.
URL https://www.sciencedirect.com/science/article/pii/S2405896321008521

[13] A. Singh, P. Gupta, M. Asjad, Reconfigurable manufacturing system (rms): Accelerate towards industries 4.0, SSRN Electronic Journal (01 2019). doi:10.2139/ssrn.3354485.

[14] R. Adamietz, T. Giesen, P. Mayer, A. Johnson, R. Bibb, C. Seifarth, Reconfigurable and transportable container-integrated production system, Robotics and Computer-Integrated Manufacturing 53 (2018) 1–20. doi:https://doi.org/10.1016/j.rcim.2018.02.008.
URL https://www.sciencedirect.com/science/article/pii/S0736584517301515

[15] H. Arnarson, H. Mahdi, B. Solvang, B. A. Bremdal, Towards automatic configuration and programming of a manufacturing cell, Journal of Manufacturing Systems 64 (2022) 225–235. doi:https://doi.org/10.1016/j.jmsy.2022.06.005.
URL https://www.sciencedirect.com/science/article/pii/S0278612522001005

[16] S. Sahoo, C.-Y. Lo, Smart manufacturing powered by recent technological advancements: A review, Journal of Manufacturing Systems 64 (2022) 236–250. doi:https://doi.org/10.1016/j.jmsy.2022.06.008.
URL https://www.sciencedirect.com/science/article/pii/S0278612522001042

[17] Q. Zhu, S. Huang, G. Wang, S. K. Moghaddam, Y. Lu, Y. Yan, Dynamic reconfiguration optimization of intelligent manufacturing system with human-robot collaboration based on digital twin, Journal of Manufacturing Systems 65 (2022) 330–338. doi:https://doi.org/10.1016/j.jmsy.2022.09.021.
URL https://www.sciencedirect.com/science/article/pii/S0278612522001704

[18] B. Wang, F. Tao, X. Fang, C. Liu, Y. Liu, T. Freiheit, Smart manufacturing and intelligent manufacturing: A comparative review, Engineering 7 (6) (2021) 738–757. doi:https://doi.org/10.1016/j.eng.2020.07.017.
URL https://www.sciencedirect.com/science/article/pii/S2095809920302502

[19] K. Khanna, R. Kumar, Reconfigurable manufacturing system: a state-of-the-art review, BENCHMARKING-AN INTERNATIONAL JOURNAL 26 (8) (2019) 2608–2635. doi:10.1108/BIJ-05-2018-0140.

[20] A. Singh, S. Gupta, M. Asjad, P. Gupta, Reconfigurable manufacturing systems: journey and the road ahead, INTERNATIONAL JOURNAL OF SYSTEM ASSURANCE ENGINEERING AND MANAGEMENT 8 (2, 2) (2017) 1849–1857. doi:10.1007/s13198-017-0610-z.

[21] J. Morgan, M. Halton, Y. Qiao, J. G. Breslin, Industry 4.0 smart reconfigurable manufacturing machines, Journal of Manufacturing Systems 59 (2021) 481–506. doi:https://doi.org/10.1016/j.jmsy.2021.03.001.
URL https://www.sciencedirect.com/science/article/pii/S027861252100056X

[22] W. Chen, Intelligent manufacturing production line data monitoring system for industrial internet of things, Computer Communications 151 (2020) 31–41. doi:https://doi.org/10.1016/j.comcom.2019.12.035.
URL https://www.sciencedirect.com/science/article/pii/S0140366419315518

[23] H. Tang, D. Li, J. Wan, M. Imran, M. Shoaib, A reconfigurable method for intelligent manufacturing based on industrial cloud and edge intelligence, IEEE Internet of Things Journal 7 (5) (2020) 4248–4259. doi:10.1109/JIOT.2019.2950048.

[24] J. Cheng, H. Zhang, F. Tao, C.-F. Juang, Dt-ii:digital twin enhanced industrial internet reference framework towards smart manufacturing, Robotics and Computer-Integrated Manufacturing 62 (2020) 101881. doi:https://doi.org/10.1016/j.rcim.2019.101881.
URL https://www.sciencedirect.com/science/article/pii/S0736584519300602

[25] Y. Li, Q. Zhang, H. Xu, E. Lim, J. Sun, Virtual monitoring system for a robotic manufacturing station in intelligent manufacturing based on unity 3d and ros, Materials Today: Proceedings (2022). doi:https://doi.org/10.1016/j.matpr.2022.08.486.
URL https://www.sciencedirect.com/science/article/pii/S2214785322057200

[26] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, X. Xu, Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues, Robotics and Computer-Integrated Manufacturing 61 (2020) 101837. doi:https://doi.org/10.1016/j.rcim.2019.101837.
URL https://www.sciencedirect.com/science/article/pii/S0736584519302480

[27] Y. G. Kim, S. Lee, J. Son, H. Bae, B. D. Chung, Multi-agent system and reinforcement learning approach for distributed intelligence in a flexible smart manufacturing system, Journal of Manufacturing Systems 57 (2020) 440–450. doi:https://doi.org/10.1016/j.jmsy.2020.11.004.
URL https://www.sciencedirect.com/science/article/pii/S0278612520301916

[28] H. Zhang, L. Z. Liu, H. Xie, Y. Jiang, J. Zhou, Y. Wang, Deep learning-based robot vision: High-end tools for smart manufacturing, IEEE Instrumentation & Measurement Magazine 25 (2) (2022) 27–35. doi:10.1109/MIM.2022.9756392.

[29] Z. Li, F. Liu, W. Yang, S. Peng, J. Zhou, A survey of convolutional neural networks: Analysis, applications, and prospects, IEEE Transactions on Neural Networks and Learning Systems 33 (12) (2022) 6999–7019. doi:10.1109/TNNLS.2021.3084827.

[30] M. Verana, C. I. Nwakanma, J. M. Lee, D. S. Kim, Deep learning-based 3d printer fault detection, in: 2021 Twelfth International Conference on Ubiquitous and Future Networks (ICUFN), 2021, pp. 99–102. doi:10.1109/ICUFN49451.2021.9528692.

[31] L. Haghnegahdar, S. Joshi, N. Dahotre, From iot-based cloud manufacturing approach to intelligent additive manufacturing: industrial

internet of things—an overview, The International Journal of Advanced Manufacturing Technology 119 (2022) 1–18. doi:10.1007/s00170-021-08436-x.

[32] R. Y. Zhong, X. Xu, E. Klotz, S. T. Newman, Intelligent manufacturing in the context of industry 4.0: A review, Engineering 3 (5) (2017) 616–630. doi:https://doi.org/10.1016/J.ENG.2017.05.015.
URL https://www.sciencedirect.com/science/article/pii/S2095809917307130

[33] S. Lee, K. Ryu, Development of the architecture and reconfiguration methods for the smart, self-reconfigurable manufacturing system, Applied Sciences 12 (10) (2022). doi:10.3390/app12105172.
URL https://www.mdpi.com/2076-3417/12/10/5172

[34] J. Friederich, D. P. Francis, S. Lazarova-Molnar, N. Mohamed, A framework for data-driven digital twins of smart manufacturing systems, Computers in Industry 136 (2022) 103586. doi:https://doi.org/10.1016/j.compind.2021.103586.
URL https://www.sciencedirect.com/science/article/pii/S0166361521001937

[35] V. Madhavadas, D. Srivastava, U. Chadha, S. Aravind Raj, M. T. H. Sultan, F. S. Shahar, A. U. M. Shah, A review on metal additive manufacturing for intricately shaped aerospace components, CIRP Journal of Manufacturing Science and Technology 39 (2022) 18–36. doi:https://doi.org/10.1016/j.cirpj.2022.07.005.
URL https://www.sciencedirect.com/science/article/pii/S1755581722001304

[36] Z. Liu, Q. Liu, W. Xu, L. Wang, Z. Zhou, Robot learning towards smart robotic manufacturing: A review, Robotics and Computer-Integrated Manufacturing 77 (2022) 102360. doi:https://doi.org/10.1016/j.rcim.2022.102360.
URL https://www.sciencedirect.com/science/article/pii/S0736584522000485

[37] J.-Y. Zhu, T. Park, P. Isola, A. A. Efros, Unpaired image-to-image translation using cycle-consistent adversarial networks (2017). doi:10.48550/ARXIV.1703.10593.
URL https://arxiv.org/abs/1703.10593

[38] H. Arnarson, B. Arild Bremdal, M. Fredheim Hanssen, Towards automatic generation of image recognition models for industrial robot arms, in: 2023 27th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), 2023. doi:Accepted.

[39] M. Khan, X. Wu, X. Xu, W. Dou, Big data challenges and opportunities in the hype of industry 4.0, in: 2017 IEEE International Conference on Communications (ICC), 2017, pp. 1–6. doi:10.1109/ICC.2017.7996801.

[40] H. Arnarson, H. Yu, M. M. Olavsbråten, B. A. Bremdal, B. Solvang, Towards smart layout design for a reconfigurable manufacturing system, Journal of Manufacturing Systems 68 (2023) 354–367. doi:https://doi.org/10.1016/j.jmsy.2023.03.012.
URL https://www.sciencedirect.com/science/article/pii/S0278612523000638

[41] J. Fahlström, G. Sziebig, Automated stacking and screwing of low volume electromechanical products with industrial robot, in: 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE), 2020, pp. 525–529. doi:10.1109/ISIE45063.2020.9152439.

[42] T. Rusch, J. Steuer, M. König, R. Sochor, K. Fink, B. Stelzle, M. Romanelli, F. Kerber, Tool-based automatic generation of digital assembly instructions, Procedia CIRP 99 (2021) 454–459, 14th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 15-17 July 2020. doi:https://doi.org/10.1016/j.procir.2021.03.065.
URL https://www.sciencedirect.com/science/article/pii/S2212827121003462

[43] H. Al-Sahaf, Y. Bi, Q. Chen, A. Lensen, Y. Mei, Y. Sun, B. Tran, B. Xue, M. Zhang, A survey on evolutionary machine learning, Journal of the Royal Society of New Zealand 49 (2) (2019) 205–228. arXiv:https://doi.org/10.1080/03036758.2019.1609052, doi:10.1080/03036758.2019.1609052.
URL https://doi.org/10.1080/03036758.2019.1609052

[44] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: Nsga-ii, IEEE Transactions on Evolutionary Computation 6 (2) (2002) 182–197. doi:10.1109/4235.996017.

[45] H. Arnarson, B. Arild Bremdal, B. Solvang, Reconfigurable manufacturing: Towards an industrial big data approach, in: 2022 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), 2022, pp. 632–637. doi:10.1109/AIM52237.2022.9863341.