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RESEARCH ARTICLE

Industrial mobile robot-based manufacturing system modeling potential

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Abstract

Industrial mobile robots as service units will be increasingly used in the future in factories with Industry 4.0 production cells in an island-like manner. The differences between the mobile robots available on the market make it necessary to help the optimal selection and use of these robots. In this article, we present a concept that focuses on the mobile robot as a way to investigate the manufacturing system. This approach will help to find the optimal solution when selecting robots. With the parameters that can be included, the robot can be characterized in the manufacturing system environment, making it much easier to express and compute capacity, performance, and efficiency characteristics compared to previous models. In this article, we also present a case study based on the outlined method, which investigates the robot utilization as a function of battery capacity and the number of packages to be transported.

Impact Statement

The number of industrial mobile robots available on the market for manufacturing systems is constantly increasing. Manufacturing systems are described analytically for the simpler cases, and more typically using simulation software for the more complex applications. The iteration thus achieved eventually leads to a close to optimal result. The mobile robot-centric manufacturing system outlined in this article gives the possibility to formulate the whole task from the mobile robot perspective, so that mainly the properties of these devices need to be considered for the selection.

1. Introduction

Use of industrial mobile robots is becoming more and more common in modern manufacturing systems, especially in factories with island production cells that meet Industry 4.0 requirements. The mobile robot is usually seen as a serving unit, a device for material handling. In this article, we outline an approach where the mobile robot is the central element and the transport tasks are described in a much simpler way compared to previous models.

The study is motivated by the increasing trend of mobile robots and the fact that the selection of mobile robots to be integrated into manufacturing systems is simulation based and very time-consuming. The aim is to construct a simple model that describes the manufacturing system from the perspective of the mobile robot and thus can be rapidly calculated and the results obtained quickly. The article describes a theory concept, enhanced by a practical case study.

Industrial mobile robots are available from a wide range of manufacturers. Some companies specialize only in this area, larger players usually include these devices in their product range through acquisitions. The range varies from smaller or simpler automated guided vehicle (AGV) robots to more complex, intelligent mobile platforms with higher payloads (Oyekanlu et al., 2020).

An AGV, also known as an autonomous mobile robot (AMR), is a mobile platform that navigates along a predetermined path by means of a wire, painted or glued strip, or magnetic tape embedded in the floor (Hines, 2021). Other solutions are also available using radio waves, lasers, or built-in image recognition systems for automated path planning. They are widely used in industrial installations and warehouses for moving heavy loads. Their application almost exploded at the end of the 20th century. Some of them carry loads that can be anything from raw materials to finished products, while others pull these in cargoes. These devices are also known by other names: the laser-guided vehicle (LGV), or the cheaper versions: automated guided carts (AGC). The term AMR is widely used nowadays to refer to vehicles that do not require external navigation infrastructure (wire in the floor). The short article from Hines also mentions the possibility of manual or automatic battery exchange as a possible direction for operational reliability.

AGVs were first introduced in 1955 and since then they have developed massively (Fazlollahtabar and Saidi-Mehrabad, 2015). Their applications and types have grown and are still growing significantly. There are both outdoor and indoor applications, including in manufacturing, distribution, package delivery, wherever patterns can be used to organize the transportation work. According to a 2000 publication (on the research mentioned in the article of Saidi—Mehrabad) 20,000 units AGVs were used in industry. Adding to the 2015 figure, the increase is significant, as the International Federation of Robotics report for 2024 shows a 35% increase in the number of transport and logistics robots, with 1,13,000 units in 2023. The differences between the old and the newer types of AGVs concern the number of AGVs, the number of transport tasks, the degree of utilization of AGVs, the distance travelled, and the number of pick-up and delivery points. Development of new analytical and simulation models is needed that can overcome the huge computational time requirements, deadlocks, system latencies, and limited design horizons due to NP-hard problems (problems that cannot be solved in polynomial time).

There have been many studies on energizing mobile robots, of more than 140 in total by Muhammad and his coresearchers (Farooq et al., 2023). Looking at several optimization studies, there are several problems with the solutions offered: first, they are robot specific, applicable only to the robot in use, and second, they represent a compromise between economy and function, while affecting the cost of the robot only to a negligible extent. In the article, they suggest further developments to solve the problem of continuous power supply for autonomous robots, such solutions are energy mining, energy cycling, and monopropellants. The goal is to provide the next generations of robots with a clean, robust, and long-lasting energy source.

The toolbox for dynamic simulation of robots has grown in recent years. In their study, Farley et al. (2022) wrote a quantitative comparative study of a Husky A200 robot under simulated and real conditions, with objective comparisons. The test environment consisted of three types of terrain profiles, grass, bumps, and gravel, and the accuracy of speed and acceleration were investigated. Other sensors such as Lidar were not included in the analysis, this may be the subject of future research. Their results showed that CoppeliaSim performed best, followed slightly behind by Gazebo.

When using mobile robots, many vehicles and many tasks have to be handled at the same time, which requires a very complex simulation, as studied by López et al. (2022). When analyzing the control system, a detailed simulation of each AGV is not necessary. Their achievement is an event simulator built into a framework that statistically models AGV behavior using a Petri-net-based model.

Chen et al. (2021) present a metamodel-based simulation in their article. The simulation's input data are taken from a real environment and the optimization of the number of AGVs for a given set of routes is performed. The utilization and throughput were also considered in the optimization. The authors' method performs the optimization in two steps, the first step is to determine the number of AGVs at the design level. In the second step, the operational level is optimized which takes into account the charging system dispatching, positioning, and route selection rules.

Moving robots is a major issue in mobile robotics. Any related development could be interesting for the future, depending on the challenge to be met and how it can be optimally solved. Since wheel design is a typical engineering design task, Huang et al. (2022) in their study a design of a screw-propelled wheel using the deep generative model (DGM) method was implemented. The designed model was 3D printed and tested in comparison with a conventional screw-propelled wheel. The measured results showed an increase in effectiveness of 15%.

Lian et al. investigated scheduling strategies for industrial robots in a spatiotemporally constrained Industrial Cyber-Physical System (ICPS) framework (Lian et al., 2022), where the robots autonomously execute a route-finding algorithm. ICPS is an evolved structure based on the 5C (Configuration, Cognition, Cyber, Conversion, Connection). The article builds on previous research that has made significant progress in the areas of task efficiency, parking time, deadlocks, congestion mitigation, routing, collision avoidance, and safety issues. The presented multilevel strategy has significantly improved scheduling, while autonomous path planning has improved the autonomy of each robot.

In her study, Szalavetz (2022) helps to explain the fading industrial framework due to digitalization by analyzing two closely related results: first, the diffusion of general-purpose digital technologies into the resources, products, processes, value chains, and business models of traditional manufacturing industries. Second, the adaptation of traditional stakeholders to the earlier. By focusing on a specific industry, her study is intended as a springboard for research in other sectors.

In the relevant literature, we find a wide range of manufacturing system models, usually described and solved for a specific task (Kang et al., 2020). Artificial intelligence methods have been used in manufacturing processes for a while, including big data analytics, and more recently machine learning methods are being used in these areas (Gunasekaran et al., 2018). In a systematic review article, Kang et al. (2020) present current trends and point to possible future research areas. In the analysis's articles, machine learning is exploited in three areas: availability, quality, and performance. Since quality and availability are measurable, they are mainly investigated, while further research is needed on the field of performance.

Li et al. (2023) have researched deep reinforcement learning (DRL) for facilitating personalized intelligent manufacturing. In their very comprehensive review article, they identify several application examples. Among these, they highlight the requirement for industrial robots to collaborate, including dynamic reconfiguration, ubiquitous sensing, and communication across time constraints. The DRL enables accurate and fast decisions in complex situations through representation learning. In the article, which analyzed 261 relevant publications, five main categories of algorithm-driven robotic applications were identified: manipulation, motion planning, scheduling, cloud robotics, and robot–human interaction.

The article by Dahl et al. (2022) presents an interactive framework for new types of automation systems. The method is called dependence on formal constraints. This system is characterized by its increasing number of complex resources, such as cooperative and mobile robots. Controlling these demands, new methods instead of traditional algorithms to keep up with the increase in complexity. The built framework supports model-based control system management, such as robot positioning based on 3D geometries, and tool design. Based on the case study presented, the method was tested on a simulation. Constraint-based descriptive models require a formal model of resources, which is identified as a bottleneck by the authors of this article. The role of the automation engineer, instead of traditional programming, will be to write specifications according to the method. In this way, the manufacturing system can be managed in a more flexible way than previous methods.

Krüger et al. (2009) investigated how humans can cooperate with robots to achieve flexibility and divergence. The article identifies future research in various aspects of high-level hybrid assembly, such as safety engineering, load reduction, and the coordination of the work of multiple operators and multiple machines.

Jahed and Tavakkoli-Moghaddam (2020) investigated a mathematical model that considers material handling systems as an intelligent transport system operated by AGVs. In their proposal, failures are also modeled, that is, several AGVs can fail simultaneously, which is unique in this field of research. They take into account the probability of machine and AGV failures and also show the effects of problems. The objective functions are production time, total delivery cost, and cost minimization due to delay penalty.

Koren et al. (2018) have researched reconfigurable manufacturing systems (RMS), the main goal of which is to increase the responsiveness of manufacturing systems to unpredictable changes in demand for their products. The design and operational principles of RMSs are formulated and reviewed, and the important finding of the article is that the challenges of unpredictable market demand, shorter product life cycles, greater product variety, lower production costs, and higher environmental standards are all increasing.

In their review article, Mourtzis (2020) present an overview of the history of simulation of manufacturing systems and some future development trends). They also show that developments are moving toward a more realistic simulation, either in real time or in a digital twin. In comparison, the concept presented in this article enables fast-running simulation at a much lower level, providing valuable data for the realization of robotic manufacturing systems.

In their article, Pedrielli et al. (2018) present the Discrete Event Optimization (DEO) method for modeling simulation–optimization problems and solving of the model. These methods are characterized by their two parts: an optimization module that selects the best system configuration and a simulation module that evaluates the system performance. The simulation module acts as a black box and receives as input the result from the optimization module, and this simulation result is then received as input by the optimization module.

Chen and Cheng (2021) focus on the optimization of conventional industrial robots due to the number of uncertainties and product variations in complex assembly processes. They propose a modeling methodology that builds a relationship between process parameters and system performance. Their iterative optimization algorithm is validated with two real industrial assembly flows.

Many researchers are focusing on the future of robots and their use in manufacturing systems. In their study, ElMaraghy et al. (2021). analyzes the changes on four axes: products, technology, business strategies, and production paradigms. One of their ideas is that, due to some of the problems of robots (sensor limitations from lighting conditions, real-time object detection, networking problems), the future of AI in robotics is AI applications enhanced by creative human operators. Another key idea is the use of arm-mounted effectors on mobile robots to perform certain tasks on production lines, based on sensor feedback.

Bhatta et al. (2022) observed in their earlier study of flexible production systems that research is essentially focused on stationarity, while transience is only considered for fixed configurations. In today’s changing world, demands are changing very rapidly and new modeling techniques are needed. In their study, they investigate a production system served by mobile robots, in which the metric is a so-called real-time permanent product loss (PPL), which measures the performance of the production system at a given moment in time and allows the control system to act immediately. Further research is needed to develop this kind of control.

One of the crucial points in the application of mobile robots is the distance that can be achieved due to the capacity of the battery. There is a lot of research going on in this area, as increasing the battery capacity implies an increase in the robot’s mass, so there is an overall upper limit. In their article, Sperling and Kivelä (2022) present a system in which both a battery and a supercapacitor are responsible for supplying power to the robot, called as dual-energy storage system (DESS). The robot’s control system selects the one to be used depending on the distance between the two storage locations. One result is the implementation of the concept in a mobile robot, which has been validated, and the other is the state machine model for the control method.

Hou et al. (2018) also discuss the improvement of the robot’s energy efficiency in their article. With an energy management model they developed, the robot can predict its energy consumption. The model uses sensor data as well as data from the control and motion system with specified weights. This model has been tested on a four-wheeled mobile robot and the results show that the model can successfully predict the consumption during motion and even support energy management efficiently. However, it is interesting to note that the model divides the operation into three parts: standby, startup, and running, and does not take into consideration the parameter that is commonly included: the robot's path.

In their article, Kim (2017) investigated the path planning and dispatch strategy of several mobile robots in a localized space for cooperative applications. One of the major challenges is to coordinate the movements of multiple robots and avoid interfering with human traffics, taking into account either the minimum distance travelled or the minimum time taken. A two-layered route planning strategy has been proposed, the first level searches for initial solutions without obstacles, and the second level tones the paths fine when dynamic obstacles are present. The method has been effectively tested on large-scale tasks with simulations.

Zhang et al. (2018) summarized the methods that have been used in path planning. They also present the genetic algorithm (GA), particle swarm optimization algorithm (PSO), artificial potential field (APF), and ant colony algorithm (ACO) strategies. Finally, recommendations for future research were made. Since each method is suitable for different applications, there is no universal algorithm that can handle all the cases discussed. Research is also needed on task organization, communication, and cooperation of multirobot systems, as well as route planning at high dimension.

As we expect to use mobile robots in a variety of environments, it is also worth taking into account some practical experience with their application. Such an application is presented in the article by Szrek et al. (2022), in which a mobile robot unit is used to monitor the state of physical objects, more specifically the state of a conveyor belt. Sensor data such as RGB image, sound, gas, and so forth, are collected. In the test, a 60-m predefined path was covered with the robot and it was found that at lower speed the path was better maintained, but for most of the duration of the experiment, the deviation was no greater than ±0.02 m.

The system presented in Li et al.'s (2021) article analyses RMFS in high-density storage warehouses where space is limited or expensive. The idea is to combine traditional RMFS and puzzle-based storage system (RMFS). The results show that the high-density warehouse layout can save about 10% of warehouse space with the same energy consumption and robot utilization. The article also suggests that the problem could be solved by applying machine learning techniques.

Tan et al. (2021) investigated an automatic vertical sorting system in their study. They described the problem using a mixed integer linear programming model, in which they considered destination stations, destinations, pick-up stations, and AGVs, and the objective function was to minimize the total sorting time. The applied particle swarm optimization algorithm solved the problem with high efficiency as demonstrated by numerical experimental results.

Tiacci's (2020) article presents a novel event-based simulation system that uses an object-oriented approach. Modeling complex systems in an object-oriented way allows the description of system dynamics in terms of interactions between objects. The event-based graph formalism is not suitable for object-oriented and component-based simulations, where the state of the system is divided into components that implement their own behavior and interact with each other. Event graphs describe the changes in state variables as events occur. In the approach discussed in the article, the state variables are associated with objects, making the model more understandable, which is particularly useful for large complex systems.

The dynamic flexible manufacturing environment poses many challenges (unexpected pedestrian traffic, collisions, fast and slow zones, space for robots, and so on) to the movement of mobile robots, which can lead to delays even when travelling a simple route (Liaqat et al., 2019). In their article, Liaqat et al. developed and analyzed a new protocol that controls the movement of each robot when encountering mobile robots to ensure fast and safe passage. They set up a model, refined by a series of experiments with real mobile robots, making the model even more accurate in describing the real behavior of mobile robots.

Models are basically built using one of two approaches: either by applying some physical laws, or by self-learning based on data. While in the first case, the internal workings of the model are clear, in the second case, we are describing a behavior that is black-box like. Retzler et al. (2024) have combined these two methods in order to complement the errors of the physical parametric model (e.g., incomplete

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description of complex behaviors, noise) with data analysis-based methods. The physical interpretation of the system structure contributes significantly to improving the accuracy of black-box models.

Robots are used for many tasks in addition to the industrial transport tasks discussed in this article. Each area is not necessarily closely related to the others, but it may be worth looking at other applications, as valuable ideas can be transferred. One such area is additive manufacturing, which could play an important role in the integration of industrial robots into manufacturing systems. An interesting concept is presented in an article by Safeea et al. (2022). They have developed a collaborative robot 3D printer. The presented framework covers both hardware and software parts from the CAD model to the finished product. The implemented inverse kinematics avoids singularities due to the redundancies of the robot joints. The result is that the resulting printed parts have 25% stronger mechanical properties.

The current fourth industrial revolution is also contributing to the spread of robots, so this area should also be addressed when discussing industrial robots. One of the highly expected technologies is digital twins, from which an interesting study has also been highlighted. In their study, Culot et al. (2020) aim at a better understanding of the whole concept of Industry 4.0, reducing the confusion around the definition, which is increased by newer and newer names such as the fourth industrial revolution, smart manufacturing. In this article, previous articles are grouped according to the various keywords and from this a system of interpretation is built. They identify four types of key technologies: interfaces between the physical and digital worlds, networks, data analysis, and digital–physical process technologies.

In the future, one of the keys to control manufacturing systems could be digital twins, as researched byLiu et al. (2023). They innovated the concept with a decision process based on virtual entities. They called this the digital-twin-based manufacturing system (DTMS), and decision making by these entities is a key factor affecting the accuracy of the system. The decision model must react to the state changes in real time. Inspired by biology, a mechanism that imitates instinct and learning behaviors was investigated. Finally, they propose a rule-driven decision mechanism instead of instinct-driven and conclude that learning decision mechanisms are the next potential research direction.

Balancing is a key factor for efficiency in industrial mobile robotic assembly systems, and it is therefore necessary to explore the state of the art in this field (Huo and Lee, 2021). In their article, Jiage et al. analyzed an intelligent automation controlled production line that responds to unexpected events. Real-time information from the assembly line is used for adaptive decision making, which is controlled by a fuzzy control system, resulting in improved performance of the assembly process.

Li et al. propose a novel algorithm to maximize the productivity of AGVs (capable of carrying multiple loads simultaneously) in FMS manufacturing systems (Li and Kuhl, 2017). PDER (pickup-or-delivery-on-route) is an algorithm that selects a “low-cost” task (that is physically close to the robot) based on its current position. The algorithm allows robots that are not fully loaded to pick up another product and move on to their next destination. This is due to the fact that PDER prioritizes the movement of parts ready for further machining over the transport of finished parts.

The problem with using the ant colony algorithm in mobile robot path planning is that previously explored paths cannot be fully used. Hence, Hou et al. (2022) have constructed and tested an improved algorithm in their article. The authors have developed and tested a faster converging version of the ant colony algorithm, enhanced with a modified roulette method. The modification consisted in making the value of the probability variable (multiplier) influenceable by another variable. They analyzed deadlock problems and developed specific strategies to avoid them, which penalize paths that reach deadlock, so that the path’s pheromone value is volatilized.

Viharos and Németh (2018) used the software Plant Simulation to study a manufacturing system supported by AGVs using discrete event systems or DES. Four types of products are transported between stations and buffers by two robots. The analysis of the production system in two different layouts is supported by a graphical interface. Future directions for improvement are mentioned: extending the unit load of the robots to multiple loads; handling uncertainties such as downtime with probabilistic variables; maintenance prediction; and product order prioritization.

For mobile robots, the issue of path planning always arises, and there is a lot of research on this topic (Abdallaoui et al., 2022). In their article, Abdallaoui et al. review the algorithms used for path planning, grouping them into five categories according to their type: sampling algorithms, node optimal algorithms, mathematical model-based algorithms, bio-inspired algorithms including neural networks, and finally multisession algorithms. The algorithms include traditional Dijkstra, genetic algorithm, and neural network learning. The advantages and disadvantages of each algorithm are analyzed in detail and their performance is compared, leading to the conclusion that the use of a single approach is not sufficient to achieve vehicle navigation. The best solution is achieved by a fusion method that combines two or more approaches.

Previous research by the authors of this article have already analyzed a novel approach to mobile robot modeling in manufacturing systems (Boleraczki and Gyurika, 2020). A solution to the mobile robot transportation problem modeled with Petri nets is presented. In addition to the start and destination positions, the robot states were characterized by the states of cargo loading, travel, and battery charging.

2. The mobile robot-centric model

The motivation for this article is the authors' view of the mobile robot-centric manufacturing system concept published in this article as part of a complex system development. The aim is to simplify manufacturing systems in such a way that mobile robots are seen as the critical and only functional unit of the manufacturing system. This is a novelty compared to previous approaches discussed in the literature. The goal is to create a modeling concept that does not require external software and prescribed simulation routines. It does not use an external library, nor does it require competence in other simulation systems. Although very complex systems are available (visual components, plant simulation), they are expensive and require a high level of expertise, and the results cannot be freely manipulated, except in the structure used by these systems. The concept presented in this article, in contrast, puts the mobile robot at the center and looks at the manufacturing system from this perspective. This has its limitations and its potentials, since a state machine can be turned into a single program, which the programmer can freely shape and extract any relevant data. For future research, several versions of manufacturing systems can be produced in a short time based on this system and used as input data for other simulations.

There are many ways to describe production systems, but these are not entirely optimal for a mobile robot. Therefore, when prescribing the model, the aim should be to obtain a system that is easy to use for the three main tasks of the mobile robot (task assignment, route planning, traffic control). There are several possible specifications, the two most common ones are: discrete event system and linear programming. The presented comprehensive modeling method supports mainly the implementation with discrete event modeling options. It can handle more complex models than linear programming equation and provides an optimal solution in a reasonable time. The parts of the method are: mobile robot description, manufacturing system characteristics modeling, and mobile robot task description.

Consider the set R as the set of robots, with element number i.

Each R_i has a possible number j of features, denoted with R_{ij}.

This allows the properties of the robots to be named and managed. Some robot properties are: maximum robot speed, load capacity, dimensions, turning area requirement, battery capacity.

Let the set of production equipment (e.g., machine tools or assembly machines) in the production system be M, the number of machines is set to k, each property is set to l, and each property of each machine is denoted by M_{kl}. Some possible properties are: minimum cycle time, number of pieces that can be produced in a given time, number of tools, size of equipment, number of connection points, position, and orientation on the floor plan.

There should also be a set of characteristic parameters of the production system, denoted by S, with the number n of parameters. The parameters listed are, for example, number and location of machines, length, and width of paths between stations.

The models that can be prescribed: discrete event systems, finite state automata, Petri nets.

The objective functions can be:

- minimize the total cost,
- maximize utilization,

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– optimize the number of robots.

The intermediate objective functions can be:

– minimize downtime due to congestion,
– avoid deadlocks,
– optimize battery capacity,
– increase performance in task execution.

The description of the Figure 1 is the following:

We first analyze the product characteristics, types, number of products, cycle time, and quality characteristics. Based on these, we will prepare the production system concept for the product. This includes the process, the machines, the tools, the layout sketch, the material, and the information flow. It also includes the handling of rejects in addition to raw materials and waste.

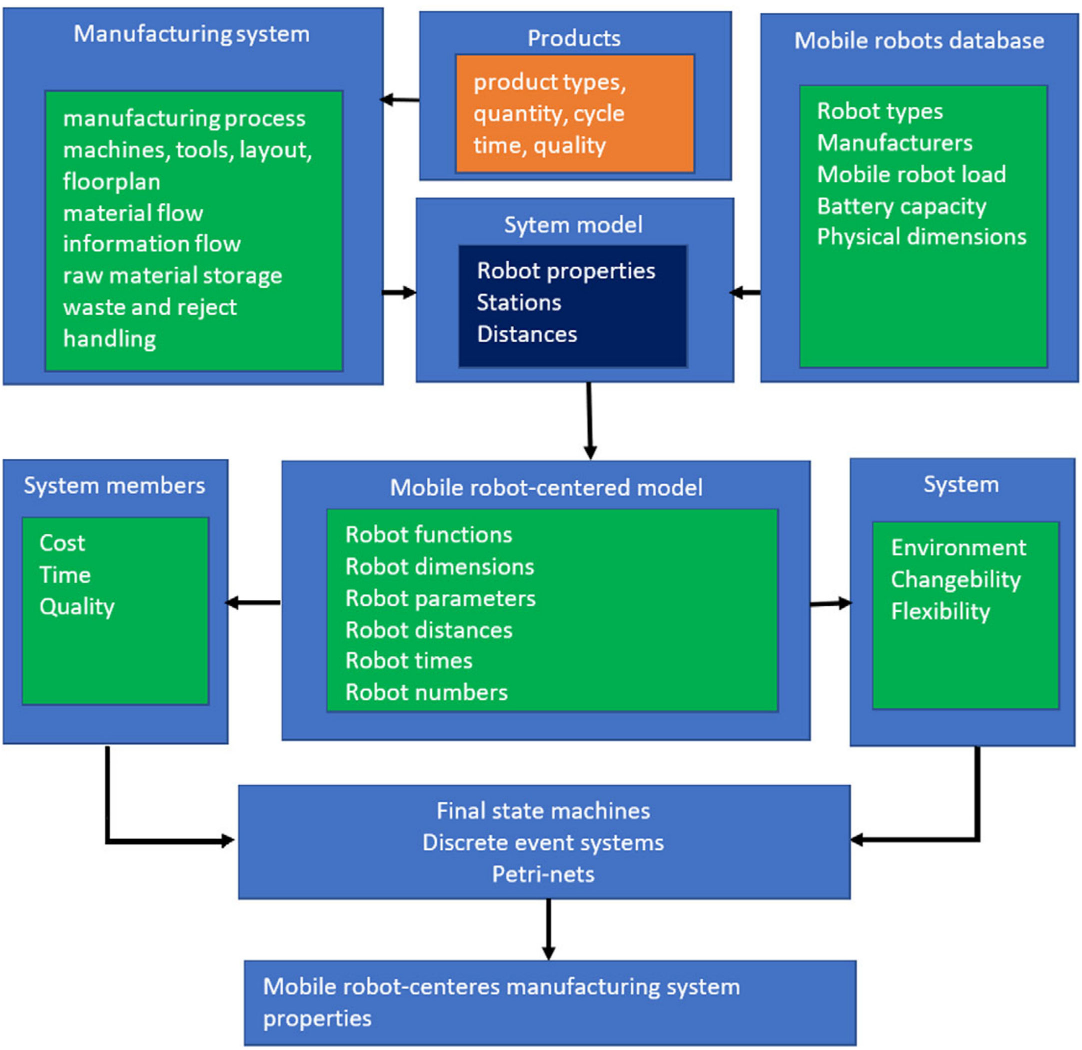

Figure 1. *The overall picture of the method.*

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In terms of creating a model system, in addition to the earlier production system description, a database of mobile robots is required, including robot types, manufacturer, load capacity, battery capacity, and physical dimensions. Furthermore, the robot properties, the stations, and their distances are also used to describe the model system.

The next step is to describe the mobile robot-centric model, which includes the relevant functions, dimensions, parameters, distances, times, and quantities. Here, all the important features of the model are defined, the distance between each station is written down (not as a number, but as a parameter), the time required to cover the distances is calculated from the robot's speed. The tasks performed by the robot, that is, the robot functions, must also be taken into account. The appearance of the available space in the model introduces another practical parameter specific to real problems, namely the consideration of physical dimensions. The number of robots is a parameter for which various optimal algorithms can be developed. The current trend is to minimize the number of robots, which may be limited by the robustness of the system requirements. Once this model is established, the parameters of the system and the system elements can be defined. Examples of the first one is the relation with the environment, the changeability, and the flexibility, while the second one is the cost, the time, and the quality.

The model written in this way is intended to be manageable with the following tools (at least one of them), so that a simulation can be created that is simple enough to handle a large number of cases in a reasonable amount of time. These tools are: Petri nets, finite state automata, discrete event systems.

Finally, from the solution of the described mobile robot-centric model, the system parameters and therefore the solutions to the problem can be extracted, from which the optimal solution can be selected that meets the given criteria.

Considering the earlier figure, and following the steps to complete the mobile robot-centric model specification, the simulation can be performed using the three methods mentioned before. Then, based on the evaluation of the results obtained, the process can be moved forward. Accept the results and proceed with the design based on them. Alternatively, new parameters can be considered and then the model and solutions can be redesigned. In other words, feedback is possible after the final result has been evaluated.

After describing the model, a case study is presented to illustrate the results achieved by applying the model.

3. First case study

The main task of industrial mobile robots is to move raw materials, work in progress, and final products through the production system. Figure 2 shows the different paths that each product has to take in the manufacturing system to become a finished product. These are marked with different colors. Each product is transported between the stations by robots.

When the product is finished with one phase, it is ready to be transferred to another processing stage. Industrial mobile robot technology may provide the optimal solution for this. Individual transport tasks can be assigned to the robots. The approach of a mobile robot-centric manufacturing system was used to describe the model, that is, the mobile robot was the central element. This case study is not intended to solve the routing and scheduling problems.

The robot model that is presented allows the parameters of the robot to be varied by using the example of a simple transport task. The expectation of this model is that mobile robots can be negotiated and compared in a uniform way, thus optimizing their selection for the given task. To this end, we first construct a model that can receive the robot parameters and tasks, simulate them in a discrete-event system, and use the results to draw inferences between the robot parameters and the manufacturing system parameters. This will allow us to optimize, among many other things, the optimal battery capacity for a given number of workpieces and distance (distance between two end points).

From the robot's point of view, this process can be simplified to implement a transport task from point A to point B. This was also used in the modeling, where a point A to point B transport task was described in a well parameterizable and fast simulation form.

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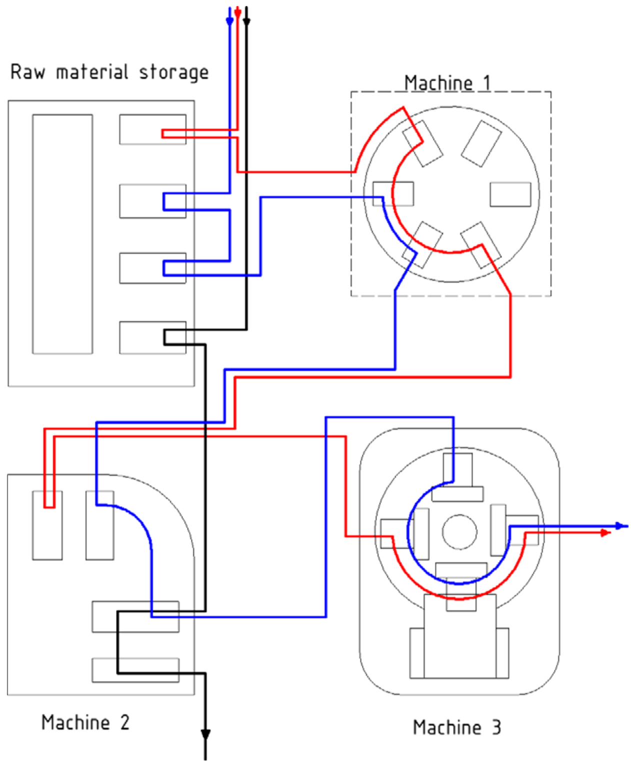

Figure 2. *A model production system with colored lines marking the path of the different products.*

The mobile robot model contains a point A and a point B. Between these, we can interpret the transport task. The operation of the model can be summarized as follows: define a given quantity of product (package) to be transported. The robot starts its operation at point A, if there is a package it picks one up. Then it moves to point B, covering the specified distance in the specified time. At point B, the robot unloads the package. It checks the battery capacity if it is enough, it returns to point A (without the package). If it is not full enough for a return trip (from B to A) and another trip from A to B, it goes to the charging point and charges the battery. At the end of the charge, it goes to point A where it checks whether there is any package to pick up. If so, it goes through the already described process again. If there is no package at point A, the delivery task is completed and the simulation ends.

The parameters of the robot are following

- Battery capacity,
- Battery loss (consumption) during movement over a unit of time,
- Charging time (battery charge time),
- If there is a package on the robot (Boolean value).

Manufacturing system characteristic:

- Number of packages,
- Distance from point A to point B,
- Distance from point B to point A,
- Distance the charging point from point B.

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The parameters used to calculate the earlier parameters are as follows:

- Number of packages: "c,"
- Delivery time A → B: "ab,"
- Delivery time B → A: "ba,"
- Charging time: "t,"
- Movement time to the charging station: "tm,"
- Utilization of the mobile robot: "K."

The task is to maximize the utilization, which can be represented by the equation (1) using the parameters above.

$$max\, K = \frac{\sum c * (ab + ba)}{\sum c * (ab + ba) + tm + t} \tag{1}$$

A finite-state automation illustrates the foundation of the simulation model for the case study described. This automation is shown in Figure 3.

The model was adapted in python programing language. For the implementation, an *if* statement is embedded in a loop that specifies which event is currently running (Table 1). In the interpretation, this was supplemented by a time factor. The time is a uniform value, each event is defined with respect to this value. The length of the paths between each station is also measured in this unit, therefore called the unit of movement (Table 1).

The results obtained show that the model can be used to test the battery capacity as a function of the number of pieces and the distance to be transported, as can be seen on Figure 4. As can be seen from the values for a smaller number of packs, the higher the capacity, the worse the utilization is because the charging time is too long compared to the number of packs, as can be seen for 100 packs and a capacity of

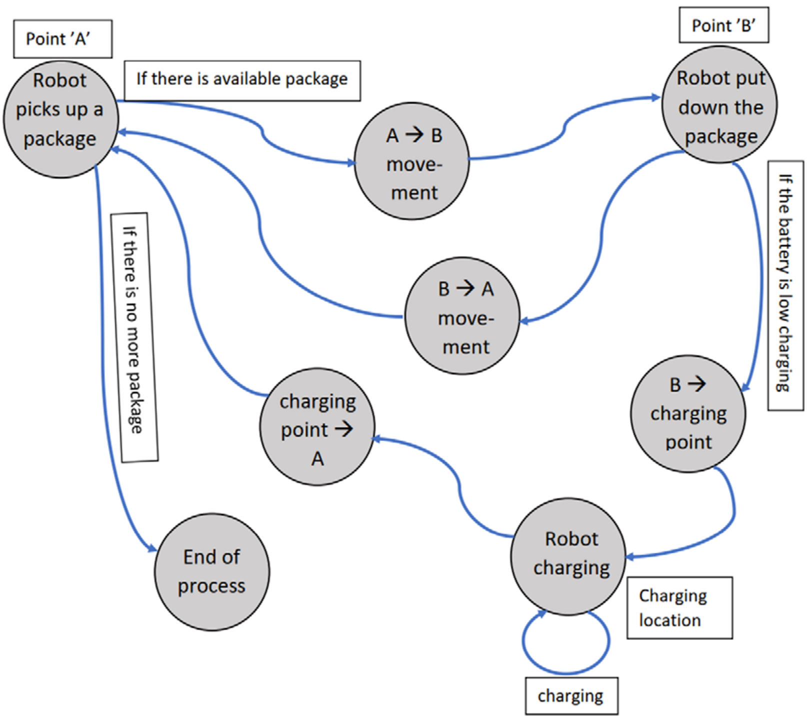

Figure 3. *The final state machine of the described system.*

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Table 1. *Source code for the final state machine*

States:

1: pick up the package
2: put down the package
3: robot moving from A to B
4: robot moving from B to A
5: robot moving from B to charging point
6: robot is charging
7: robot is moving from charging point to A
8: simulation over

i = 0 // cycle variable, using for time step
path_length_AB = 10 // the length of the path from A to B

path_length_BA = 10 // the length of the path from B to A
path_length_charging = 6 // the length of the path from B to the charging point, and from charging point to A

actual_state = 1 // starting state

packages = 1000 // how many packages are ready to move

charge = 100 // this is the capacity of the battery

robot_charge_no = 0 // charging cycle number

Python code:

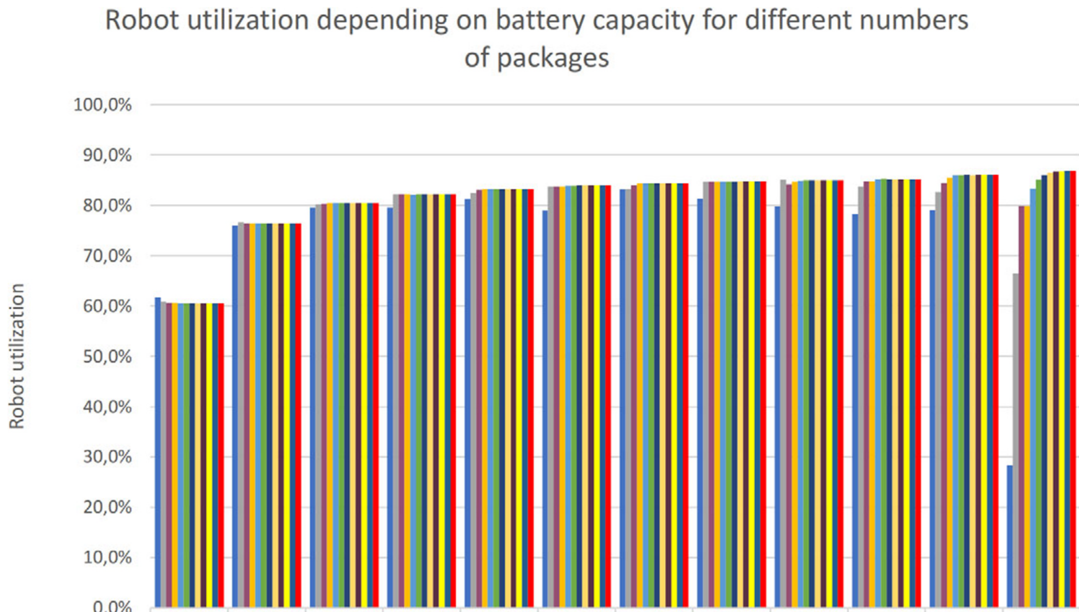
```
while state != 8:
  if state == 1:
            if A_packages > 0: // if there is available package
             A_packages - = 1 // count down the number of the package
      state = 3
      robot_all += 1
    else:
      state = 8
  if state == 2:
    B_packages += 1
    robot_all += 1
    if charge > 20: //check the battery
      state = 4
    else:
      state = 5
  if state == 3:
    if robot_i == path_length_AB:
      state = 2
      robot_i = 0
      robot_move += 1
    else:
      robot_i += 1
      charge -= 1
      robot_move += 1
  if state == 4:
    if robot_i == path_length_BA:
      state = 1
      robot_i =0
      robot_move += 1
    else:
      robot_i += 1
      charge -= 1
      robot_move += 1
  if state == 5:
    if robot_i == path_length_charging:
      state = 6
      robot_i =0
    else:
      robot_i += 1
      charge -= 1
  if state == 6:
    if charge >= max_charge–5:
      state = 7
      robot_i =0
      robot_all += 1
      robot_charge_no += 1
```

Continued

Table 1. *Continued*

```
        else:
            robot_i += 1
            charge += 5
            robot_all += 1
    if state == 7:
        if robot_i == path_length_charging:
            state = 1
            robot_i =0
        else:
            robot_i += 1
            charge - = 1

    increment i // next time step
```



	50	100	150	200	250	300	350	400	450	500	1000	10000
100 pcs	61,7%	76,0%	79,5%	79,5%	81,2%	78,9%	83,1%	81,3%	79,8%	78,2%	79,0%	28,4%
500 pcs	60,8%	76,6%	80,2%	82,2%	82,4%	83,7%	83,2%	84,6%	85,0%	83,7%	82,6%	66,5%
1000 pcs	60,6%	76,4%	80,3%	82,2%	83,0%	83,7%	83,9%	84,6%	84,1%	84,7%	84,4%	79,9%
2000 pcs	60,6%	76,4%	80,4%	82,2%	83,2%	83,7%	84,3%	84,6%	84,6%	84,7%	85,4%	79,9%
5000 pcs	60,5%	76,4%	80,4%	82,1%	83,2%	83,8%	84,3%	84,6%	84,8%	85,1%	86,0%	83,3%
10 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,8%	84,3%	84,6%	84,9%	85,2%	86,0%	85,0%
20 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,9%	84,3%	84,6%	84,9%	85,1%	86,1%	86,0%
50 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,9%	84,3%	84,7%	84,9%	85,1%	86,0%	86,5%
100 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,9%	84,3%	84,7%	84,9%	85,1%	86,1%	86,7%
200 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,9%	84,3%	84,7%	84,9%	85,1%	86,1%	86,8%
500 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,9%	84,3%	84,7%	84,9%	85,1%	86,1%	86,9%
1 000 000 pcs	60,5%	76,4%	80,4%	82,2%	83,2%	83,9%	84,3%	84,7%	84,9%	85,1%	86,1%	86,9%

Battery capacity 50 - 10000 unit of movement

Figure 4. *Results of first case study simulation.*

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10,000 unit of movement, the value is 28.4%. However, for a higher number of packages, the utilization reaches a maximum value beyond which it does not increase, 85.1% for 500 packs, 86.1% for 1000 packs, but even for 10,000 packs, it is only slightly higher: 86.9%. The model outlined is therefore suitable for comparing robot utilization rates.

3.1. Second case study

In the second case study, the model is extended to a more complex scenario. The number of stations and the number of products are increased. The concept is the following: the robot starts from a raw material warehouse to manufacture products. From there it takes the necessary raw materials and then travels to each station according to the product information. At each station, it spends a specified period of time and then moves on to the next station. From the last station, the finished product is taken to the finished goods warehouse. Here, the robot checks the battery capacity. If the battery capacity is below a threshold value, charging is required and the robot goes to the charging point, from where it returns to the raw material warehouse after charging. If no charging is required, the robot will go to the raw material warehouse instead.

In this case, there are four stations and three different products can be produced, named ABCD, ABD, and CD. At each station there is a specified time for the process to complete, for simplicity this has been set to 5 units, that is, 25 s. As these are also in separate variables, changing these values is extremely simple. Production time for each product without delivery: ABCD—100 s, ABD—75 s, CD—50 s. All the states of the whole process are represented by the state machine in Figure 5, where the states for the ABCD product range from 101 to 112. The common states for all the three products are states 113 and 114 for battery charging and states 116 and 115 for the return to the raw material warehouse. The ABD product has state numbers 201 to 209 and the CD product has state numbers 301 to 307. The longest simulation run involved the production of more than 5 million pieces, which in production time, if 75 s is applied, is more than 12 years, and this does not include the time for robotic deliveries. The run time of this program was less than 9 min.

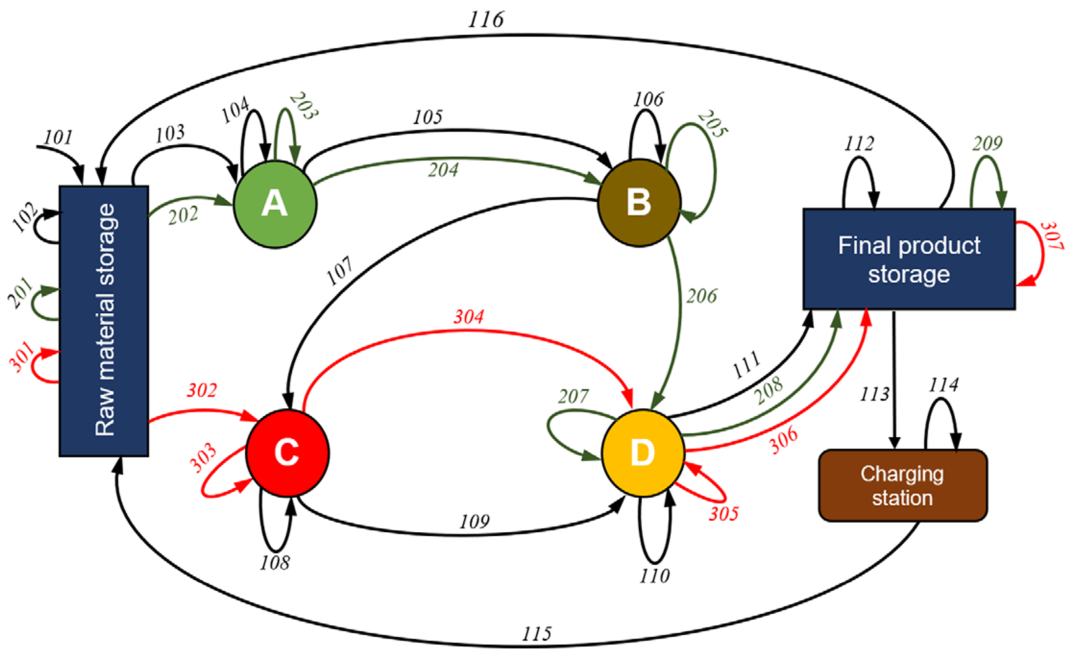

Figure 5. *The final state machine of the second case study.*

The program can be used to determine the optimal distance between machines based on the required number of different products to be produced. The optimization criteria defined in terms of the number of charges of the robot, because its value also characterizes the speed of the whole system. Thus, we want to minimize this number of charges. The distance between the machines can be placed under an optimal arrangement, if it is known how many of each part to produce. This has been done in several steps, and the following graphs on Figure 6 have been prepared by picking out a part of the results. For ease of visualization, only two distances are considered. These are RS-A (from raw material storage to point A) and CD (from point C to point D), respectively. Plotting these two distances in two dimensions, in a plane, gives the bottom plane shown in all the graphs at Figure 6. The vertical axis shows the number of charges. Three graphs show the manufacture of just one product, these are ABCD, ABD, and CD. From these, it can be seen that the manufacture of the product CD is not sensitive to changes in the distance RS-A, while the product ABD varies uniformly and is independent of changes in the distance CD, but is linearly dependent on the distance RS-A. This is only a simple example, the code implemented on the basis of the mobile robot-centric manufacturing system theory can be used to explore much more complex relationships, which are more difficult to visualize. It may be suitable, for example, to find an optimal solution for a large number of path possibilities with a minimum search.

The running times for each number of production pieces, in rounds: 100,020 pieces/23.9 s; 1,000,020 pieces/228.3 s; 20,020 pieces/4.59 s; 504,020 pieces/47.16 s; 5,040,020 pieces/533.54 s. The advantage is that the program can be easily built on the ground of the state machine, the built program is transparent and extensible.

The disadvantage is that the developer must be capable of understanding the theory of state machines in addition to the programming knowledge.

What distinguishes this whole methodology from other commercial systems are the following three things: First, it approaches the problem analytically and does not require any expensive software available

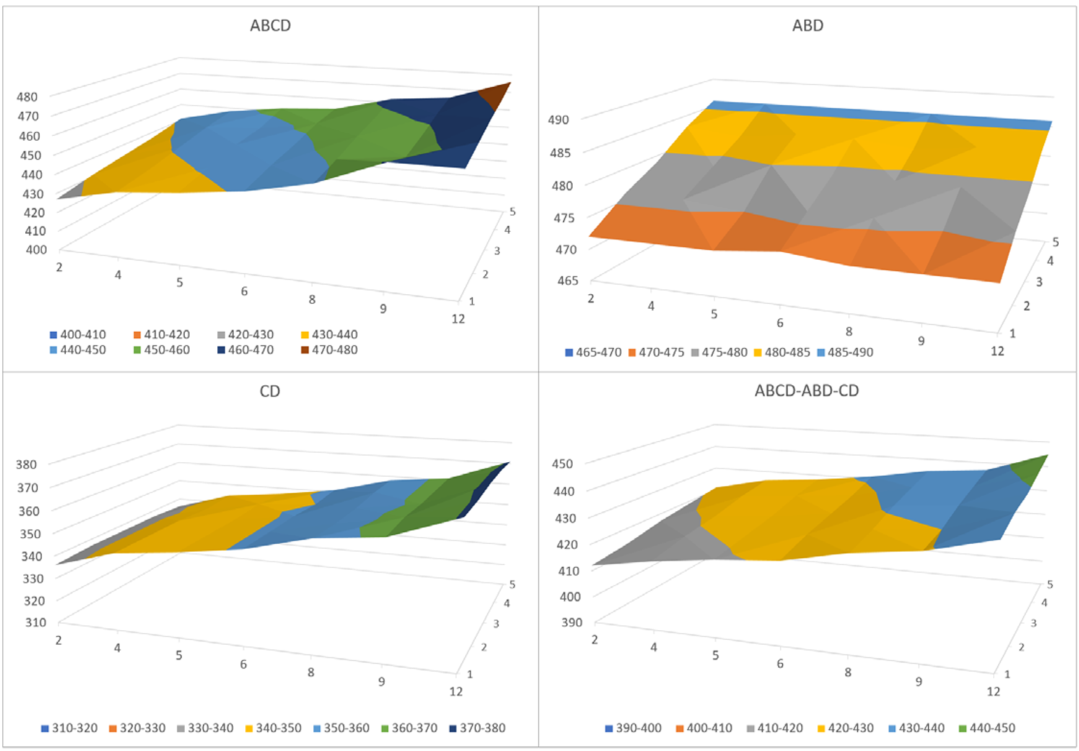

Figure 6. *Result of the second case study simulation.*

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in the industry, only basic programming knowledge. Second, because the program runs very quickly, it can simulate extremely large numbers of items very quickly, or an extremely large number of cases in a reasonable amount of time. This requires only a few parameter rewrites, which can be done automatically even in a more complex program, which automates the search for the optimum. Third, elements that more closely represent real conditions can be added to the simulation at a later stage. These can be handled by probabilistic variables, allowing, for example, the probability of breakdown of certain robot types to be included in the model. Even blockages and operator assistance can be introduced in this way.

4. Discussion

The selection and integration of mobile robots into a manufacturing system opens up many questions and challenges for engineers. Optimal use of these units can be predicted at the moment of their selection, based on measurable values and simulations. Such simulations will continue to help production system designers in the future. It is worth investigating how to write up the manufacturing system from the robot's point of view and to assist selection. Further research on this method is needed, and the implementation of existing algorithms should be investigated. It is worthwhile to complement it with a mobile robot database, which could be developed into a knowledge base to support selection. An additional idea is to analyze the simulation results using big data methods.

Based on the method, future research can be performed to investigate the return on investment, utilization, number of units required, battery capacity required, and more for simple cases of mobile robots. In addition to the selection of the optimal robot, a number of challenges can also be solved based on this concept, as demonstrated in the second case study.

5. Conclusions

The presented mobile robot-centric approach is an innovation in the literature. The mobile robot unit is either considered as part of the manufacturing system or is analyzed in isolation. The approach described will also be necessary due to the rapid growth of mobile robots and the large variety of choices expected. The aim is to ensure that the robot selected for a given task is optimal. The case study presented is an application of this approach and looks for a correlation between the number of packages to be transported and the battery capacity.

The case study described in this article confirms that the mobile robot-centric manufacturing system method is a simple way to describe practical cases and can be quickly computed. Hence, this concept can be an effective tool for modeling mobile robots embedded in the manufacturing systems in the future.

Data availability statement. The data that support the findings of this study are openly available in Zenodo at http://doi.org/, reference number: 10.5281/zenodo.15791023.

Author contribution. Based on the manufacturing simulation experience of Istvan Gyurika, Miklos Boleraczki developed the concept of the mobile robot-centric manufacturing system and performed the simulations.

Conceptualization: M.B.; Formal analysis: M.B.; Methodology: M.B.; Software: M.B.; Resources: G.G.; Supervision: G.G.; Writing – review and editing: M.B., G.G.

Competing interests. The authors declare none.

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