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OPTIMIZATION OF PRODUCTION LOGISTICS

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

Tõnis Raamets*, Jüri Majak, Kristo Karjust, Kashif Mahmood and Aigar Hermaste

Department of Mechanical and Industrial Engineering, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia

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

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

1. INTRODUCTION

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

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

* Corresponding author, tonis.raamets@taltech.ee

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

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

2. APPROACH FOR AMR PROCESS ANALYSIS AND MODIFICATION

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

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

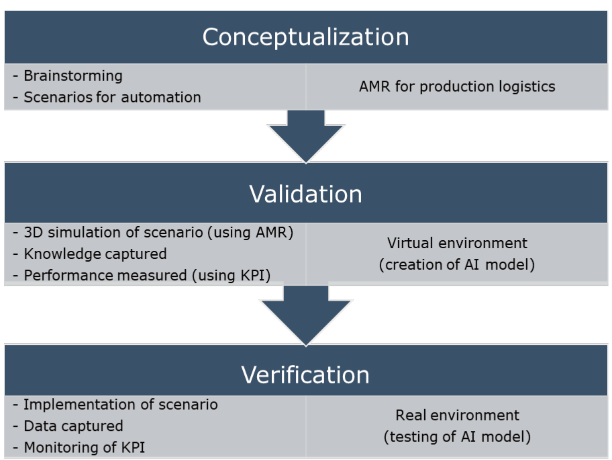

Fig. 1. Proposed approach to analyze the process of AMR for production logistics [18].

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

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

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

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

AMR path setup and routing:

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

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

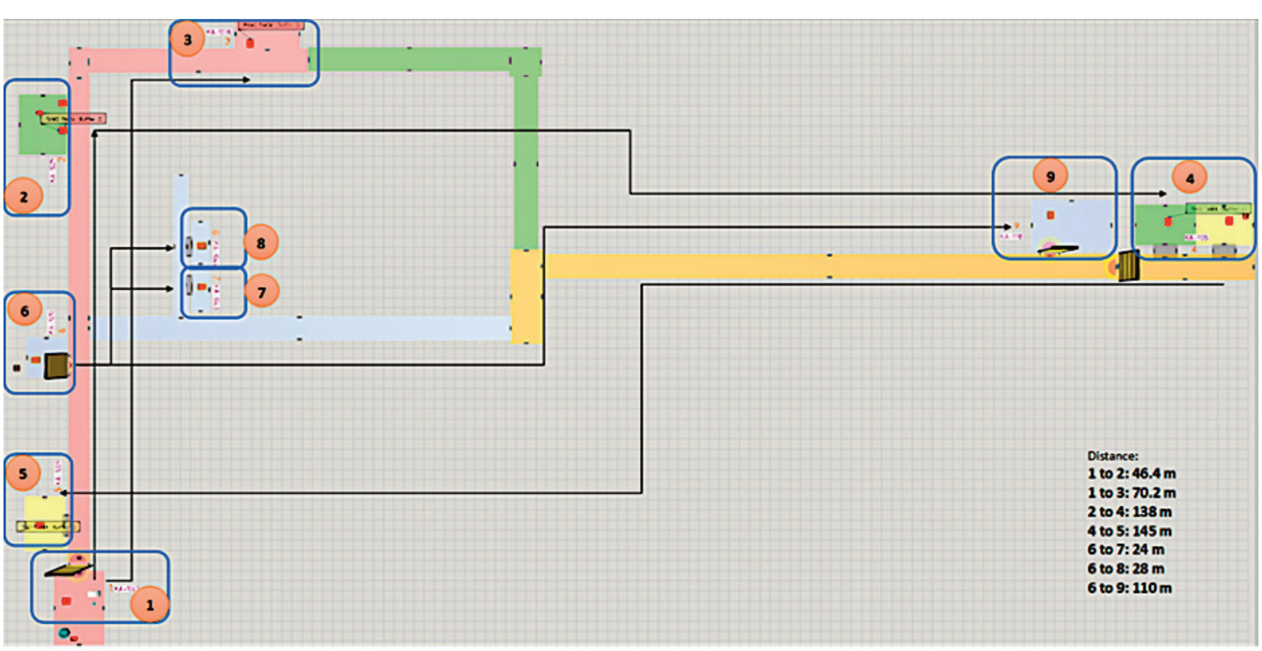

Fig. 2. AMR routing map and buffers for picking up and placing the boxes in the manufacturing area.

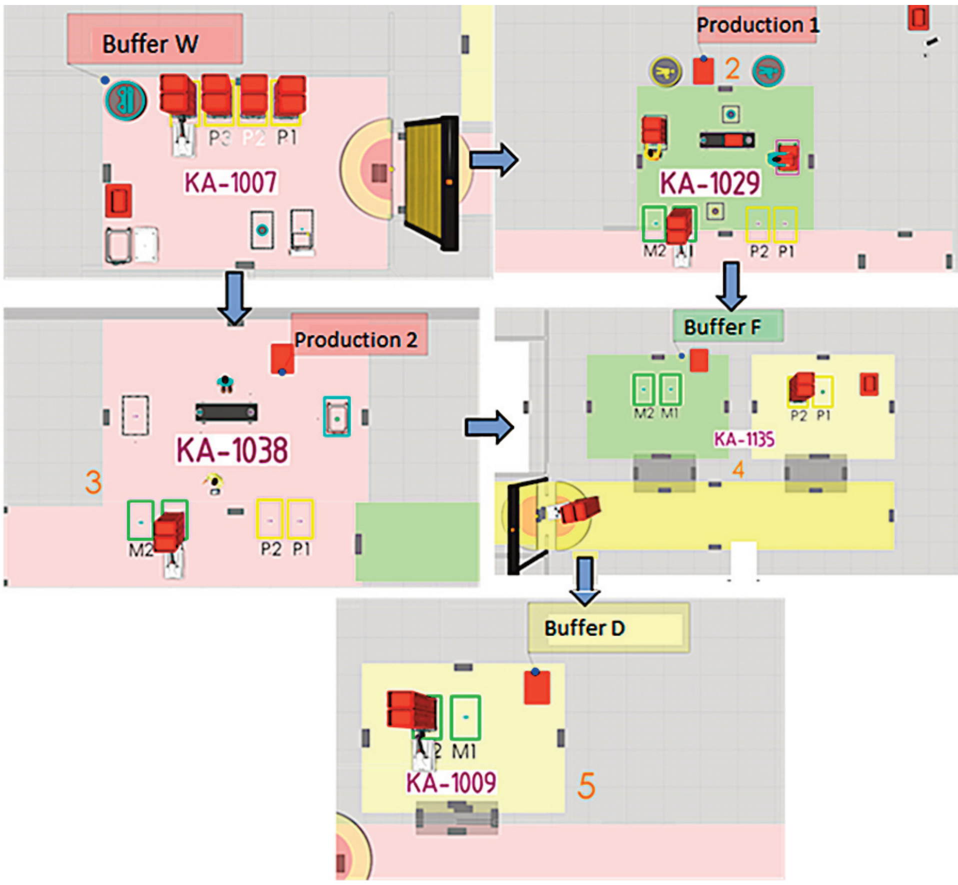

Fig. 3. AMR loading and unloading stations on the production floor.

2.2. AMR process simulation results

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

Table 1. Summary of AMR simulation analysis

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

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

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

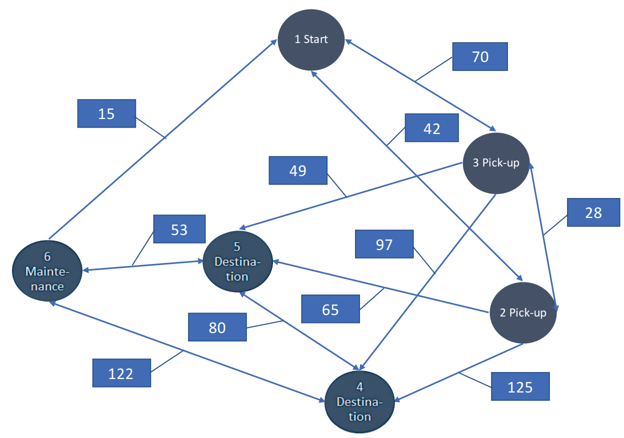

Fig. 5. AMR motion model.

3.1. Directed graph definition

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

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

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

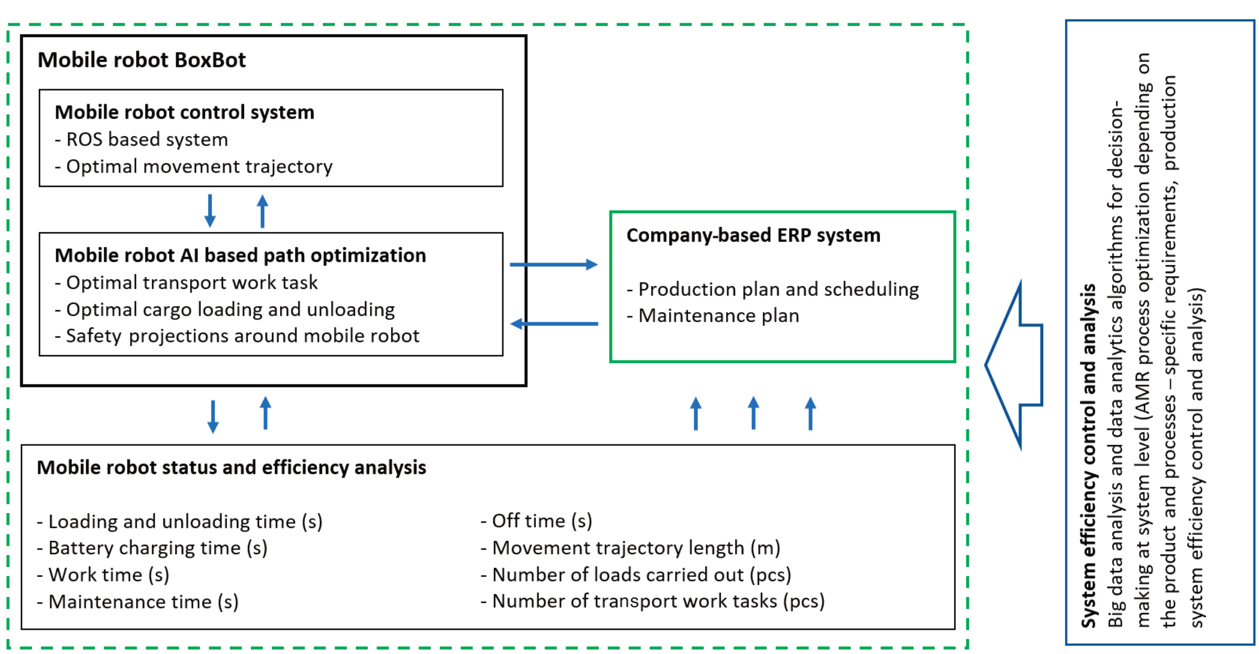

Fig. 4. General framework of the AMR data exchange.

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

3.2. Optimal path optimization

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

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

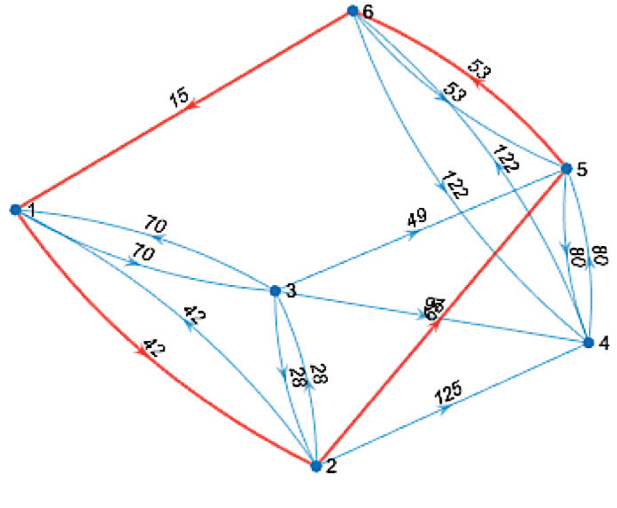

Fig. 6. The optimal path for AMR movement (mission passing loading node 2 and unloading node 5).

4. CONCLUSIONS

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

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

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

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REFERENCES

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

Autonoomsed mobiilsed robotid tootmislogistikas: protsessi optimeerimismudeli muutmine

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

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

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

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