DOI: 10.2195/lj_proc_mente_en_202410_01

Optimization model for a vehicle routing problem with cellular automated guided vehicles

Optimierungsmodell für ein Vehicle Routing Problem mit zellularen Fahrerlosen Transportfahrzeugen

Torben Mente[1]
Benjamin Küster[1]
Malte Stonis[1]
Ludger Overmeyer[1, 2]
Peter Nyhuis[1, 3]

[1]IPH – Institut für Integrierte Produktion Hannover gGmbH

[2]Leibniz Universität Hannover, Institut für Transport- und Automatisierungstechnik

[3]Leibniz Universität Hannover, Institut für Fabrikanlagen und Logistik

As the number of product variants continues to grow, the need for flexibility in intralogistics is becoming increasingly apparent. One potential solution to this challenge is the use of cellular automated guided vehicles, which can be variably interconnected depending on the size of the product to be transported. This article presents an optimization model for solving a vehicle routing problem for cellular automated guided vehicles. Furthermore, a recursive method is presented that determines an optimal transport sequence based on the solution of the model. The optimization model is implemented in a specially developed model environment and solved for a dynamic, illustrative use case. Subsequently, logistical target variables are evaluated in order to assess the solution of the optimization model. The exemplary application of the optimization model demonstrates the feasibility of modeling cellular transportation with automated guided vehicles and evaluating its performance based on logistical target variables.

[Keywords: Automated guided vehicles, cellular transport units, optimization model, simulation, logistical target values]

Mit der zunehmenden Anzahl von Produktvarianten wird der Bedarf an Flexibilität in der Intralogistik immer deutlicher. Eine mögliche Lösung für diese Herausforderung ist der Einsatz von zellularen fahrerlosen Transportfahrzeugen, die je nach Größe des zu transportierenden Produkts variabel zusammengeschaltet werden können. In diesem Artikel wird ein Optimierungsmodell zur Lösung eines Vehicle Routing Problems für zellulare fahrerlose Transportfahrzeuge vorgestellt. Außerdem wird eine rekursive Methode vorgestellt, die auf Basis der Lösung des Modells eine optimale Transportreihenfolge ermittelt. Das Optimierungsmodell wird dazu in eine eigens entwickelte Modellumgebung implementiert und für einen dynamischen, beispielhaften Anwendungsfall gelöst. Abschließend werden logistische Zielgrößen zur Bewertung der Lösung des Optimierungsmodells ausgewertet. Die exemplarische Anwendung des Optimierungsmodells zeigt, dass es möglich ist, den zellularen Transport mit fahrerlosen Transportfahrzeugen zu modellieren und den Transport mittels logistischer Zielgrößen zu bewerten.

[Schlüsselwörter: Fahrerlose Transportfahrzeuge, zellulare Transporteinheiten, Optimierungsmodell, Simulation, logistische Zielgrößen]

1 INTRODUCTION

The requirements of Industry 4.0 pose new challenges for companies in the logistics and manufacturing sectors [1]. Customized products, online trading and the just-in-time philosophy are leading to a significant increase in product diversity [2]. This leads to increasing demands on the productivity and flexibility of production and logistics processes. In order to meet these requirements, flexible transport systems are needed. In this respect, automated guided vehicles (AGV) offer solutions due to their versatility and autonomy and the ability to communicate and cooperate with information and production systems [3].

A potential limitation of AGVs is that they are often specialized in certain load carriers and therefore limited in their flexibility. To increase flexibility, cellular transport units can be used, which consist of modular, autonomously operating AGVs that can be variably combined as required [4]. These modular systems make it possible to transport products of different sizes and, thanks to their scalability, offer dynamic adaptation to varying transport volumes.

Existing development and research activities on cellular AGVs have mainly focused on the technical design and software architecture [5, 6]. Some examples include the KIVA system, KARIS PRO, the multishuttle move (MSM) and the FORMIC transport system. The KIVA system purchased by Amazon Robotics consists of a large number of vehicles that can lift individual rack units in order to transport them in a warehouse [7]. KARIS PRO is a modular AGV developed by the Institute of Materials Handling and Logistics Systems (IFL) at the Karlsruhe Institute of Technology (KIT) [8]. With the MSM research project, the Fraunhofer Institute for Material Flow and Logistics has developed a vehicle for a multimodal logistics concept that meets the requirements of cellular transportation systems [9]. The FORMIC transport system, a KIT spin-off, enables the transport of heavy loads with the help of multiple vehicles by lifting and moving the load together [10]. However, the extent to which the use of cellular AGVs is beneficial in terms of economic and logistical targets has not yet been sufficiently investigated.

A method for researching the profitability of cellular AGVs is to model the transport using the vehicle routing problem (VRP), in which the transport of products is represented using a swarm of vehicles. The standard VRP describes a mathematical optimization problem for calculating the optimal route for a specified number of vehicles to deliver to customers from a depot and was introduced in the literature by Dantzig and Ramser [11]. The model is adapted to formally map other use cases, for example by taking capacity restrictions or delivery time windows into account [12].

This article therefore presents an optimization model that can be used to represent cellular transport with AGVs. The article is structured as follows. Section 2 presents related work. Section 3 briefly explains the model environment in which the developed optimization model is integrated. Section 4 describes the problem and presents the mathematical formulation of the model. Section 5 describes the iterative formation of the transport sequence based on the results of the model and the dynamic solution approach within the model environment. Section 6 presents and evaluates logistic target variables for assessing the application of cellular AGVs. Section 7 provides the conclusion and a brief outlook.

2 Related Work

There is already a large amount of research work on modeling the transport of multiple products with AGVs [13, 14]. This includes, for example, solving an optimization model based on the VRP in order to optimize the routes of the vehicles and optimally assign the transport tasks to the vehicles. Some of the work from these research areas is presented below.

Some research work has been carried out on heterogeneous vehicle fleets in order to take into account the transportation of different products with AGVs. Qiu et al., for example, solve a heterogeneous AGV routing problem considering energy consumption along with different loading weights. They consider a pickup and delivery procedure of various products in warehouses and depots. The tasks are assigned with the aim of minimizing energy consumption [15]. Dang et al. address the problem of scheduling transportation orders on multi-load and multi-capability AGVs with battery management, where each AGV can carry more than one load at a time. Each order consists of a pickup task and a delivery task, which are associated with an origin, a destination, a soft time window and a priority [16]. In their article, Bae et al. present an optimization model and a heuristic solution approach with multiple heterogeneous AGVs, in which the route is optimized by minimizing the transport costs. The orders consists of a pickup and a delivery position and the required payload to handle the assigned products [17]. In their paper, Li and Huang study the task scheduling problem for heterogeneous AGVs, in which a warehouse assigns tasks to suitable heterogeneous AGVs to minimize the total cost, which includes the travel cost and the delay cost. To achieve this, they are using a new framework that takes route planning and task assignment into account at the same time [18]. In their paper, Wang et al. investigate the problem of task scheduling for heterogeneous AGVs in manufacturing systems, focusing on the coordination of coupled tasks that require different AGV types to cooperate. To address with these complex requirements, the authors develop a multi-decision-points model that maps different decision points along the task planning and thus enables finer control and coordination [19].

In order to take into account the transportation of different products and to enable flexible transportation, other models focus on the use of multi-load AGVs. Lin et al. study the task scheduling problem for multi-load AGVs in an automated storage and retrieval system. They develop a model that considers various task characteristics and system constraints to maximize the efficiency of the system. The authors propose the MLATSO (Multi-Load AGVs Task Scheduling Optimization) method to optimize the number of AGVs deployed, travel times, and conflicts between AGVs [20]. Chawla et al. investigate the scheduling of multi-load AGVs in a flexible manufacturing system. They propose a modified memetic particle swarm optimization (MMPSO) algorithm that combines both global and local search strategies to maximize the efficiency of AGV utilization. The algorithm aims to minimize the travel and waiting times of AGVs as well as to ensure conflict-free routing [21]. In their paper, Hu et al. investigate the conflict-free scheduling of large multi-load AGVs in a material transport system. They develop a task assignment approach based on neighborhood combinations and the shortest path principle to maximize the efficiency of AGV scheduling.

They introduce a special heuristic called Variable Neighborhood Search (VNS) to optimize task distribution and avoid deadlocks and collisions [22].

Further recent literature deals with the use of homogeneous AGVs under different constraints. Zou et al. investigate the problem of task scheduling for multiple homogeneous AGVs in a matrix manufacturing system considering both loading and maintenance requirements. They develop a mixed-integer linear programming model and a self-adaptive iterative greedy algorithm to minimize the total cost, which is composed of travel cost, penalty cost and vehicle cost [23]. Boccia et al. also include battery constraints in their model. Their approach is to determine the planning of transfer orders and loading processes of a fleet of homogeneous AGVs in such a way that the time span for the handling process is minimized [24]. Maoudj et al. study the task scheduling problem for capacity AGVs in production environments with conflicting products that cannot be transported together. The main focus is on minimizing the maximum travel distance of an AGV while considering capacity and product conflict constraints [25].

However, all the presented works do not consider the possibility of collaborative transportation of goods by multiple, homogeneous entities. On the one hand a heterogeneous fleet of vehicles is used for modeling to handle various products. On the other hand studies consider multi-load AGVs to be able to transport multiple different products at the same time and thus enable an efficient and flexible transportation process.

Further literature exists which examines the use of homogeneous AGVs with the aim of optimizing the transport process. Yet these studies include additional constraints beyond those related to collaborative transportation, such as minimizing power consumption and considering the power consumption and loading times of the AGVs. Other studies consider multi-load AGVs to be capable of transporting multiple different products simultaneously, thereby enabling an efficient and flexible transportation process.

3 Description of the Model Environment

The optimization model for cellular transport was implemented in the Python programming language with the aid of a specially developed model environment for that use case. The model environment contains a variety of objects, including products, warehouses, machines, AGVs and charging stations for the AGVs. These objects are all integrated into one unified factory. The factory is divided into grids. Figure 1 illustrates an example factory comprising six AGVs and associated charging stations, in addition to a warehouse and three machines. The machines and warehouses have inputs (red) and outputs (green), which are represented as nodes in the optimization model. In the example in Figure 1, these are nodes 6 to 13.

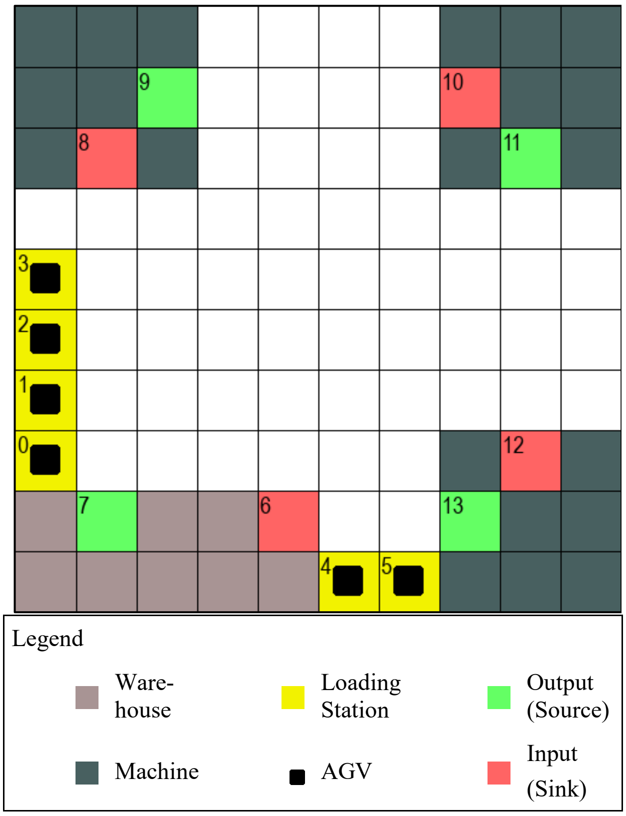

Figure 1. Model environment with objects inside the factory: six AGVs with charging stations, one warehouse and three machines, machines and warehouses have inputs (red) and outputs (green)

The model environment allows the creation of products with varying characteristics, including weight and dimensions. Warehouses can provide any number of products at a defined time interval. Machines process products within a defined time interval, thereby modifying their characteristics. Furthermore, machines possess a buffer for delivered and manufactured products. A machine that is processing a product is in the "process" state. Delivered products are then placed in the input buffer. If the output buffer is not full, finished products are transferred to it. Products are automatically removed from the input buffer for further production. If the output buffer is full and a manufacturing process is finished, the machines switch to the "blocked" status. A machine that is not producing because of lack of products is in the "idle" state.

AGVs supply the machines and warehouses with the products. Depending on the product characteristics, AGVs can be coupled to transport products that cannot be transported by a single AGV. Potential vehicle configurations for transportation include one, four, or six vehicles. In the context of the optimization model, each AGV is represented as a node. In the example factory, these representative nodes are those nodes numbered from 0 to 5 (see Figure 1).

Initially, each AGV starts at its charging station. Once a product is ready for delivery, the AGVs proceed to the designated pick-up point and load the product. The pick-up point is referred to as the source and describes the output of a warehouse or a machine. AGVs transport products to the input of warehouses and machines. Currently, the model environment does not implement a collision check, allowing AGVs to travel the shortest possible path, which is determined by the Euclidean distance. Upon arrival at the designated delivery point, the product is unloaded. Once a delivery has been completed, the AGVs are ready to commence the next order from their current location.

4 Description of the optimization model and implementation

4.1 Description of the Optimization Model

Consider a manufacturing system with k homogeneous AGVs performing pick-up and delivery jobs for specific products. Let $I = \{0, \dots, n\}$ be defined as the set of all available nodes in the underlying model. Then $K = \{0, \dots, k-1\}$ is defined as the set of all available AGVs that are also represented as nodes in the model. Thus K represents the set of all start nodes. $J = \{k, \dots, n\}$ is defined as the set of all job nodes. This corresponds to the pick-up and delivery points at the machines and warehouses. The AGVs depart from multiple positions (depots) and perform defined delivery orders from one node to another to deliver products. Initially, the starting positions of the AGVs are the charging stations. All AGVs have the same load capacity and can therefore transport products with specific characteristics (dimensions and weight). Products that are too large or too heavy to be handled by one AGV can be transported in groups of four or six vehicles. To reduce complexity, other configurations are not possible. The delivery relationships between the job nodes are known in advance and are made available to the model as a delivery matrix $Q(i,j)$. This delivery matrix also contains information on the number of AGVs required for transportation between two job nodes. It is possible for several pick-ups to be carried out from one node to different delivery locations, and a delivery location can be approached on multiple occasions from different pick-up locations.

The transportation routes are to be understood as a complete, undirected graph. This means that AGVs can move between two locations in both directions on one edge. In addition, each node is connected to every other node by an edge. The distance between two nodes corresponds to the Euclidean distance and is passed to the model as a matrix $D(i,j)$. It is assumed that the triangle inequality for the distances between the nodes is fulfilled for all vehicles.

The objective of the model is to minimize the total distance of all AGVs for the execution of delivery orders under given constraints. Each edge can be traveled on exactly once by each AGV. Once all delivery orders are completed, the AGVs stop at the job node of the last delivery.

As a solution to the model, all edges that are traveled by the AGVs are identified. The transport order is not apparent at this stage. In order to identify an optimal solution for the optimization problem, it is assumed that a sufficient number of AGVs is available. Otherwise, constraints are violated and the problem becomes infeasible.

4.2 Mathematical Formulation of the Optimization Model

For a given number of k AGVs, known delivery relationships $Q(i,j)$ between the job nodes J and a given distance $D(i,j)$ between the nodes, the following parameters and decision variables result for the optimization model.

<u>Parameters:</u>

$I = \{0, \dots, n\}$	*Set of all nodes*
$K = \{0, \dots, k-1\}$	*Set of all available AGVs, subset of I*
$J = \{k, \dots, n\}$	*Set of all job nodes, subset of I*
$D(i,j)$	*Distance between nodes i and j*
$Q(i,j)$	*Vehicle configuration between nodes i and j depending on the product to be transported*
$q_{counter}$	*Counter that counts all routes for which more than one AGV is required*
J_Q	*A set of job nodes from which more than one AGV departs*
M	*Big number*

<u>Decision variables:</u>

$x_{ijk} = \{0,1\}$	*Binary variable, 1 if vehicle k travels from node i to j, otherwise 0*
$b_j = \{0,1\}$	*Binary variable, 1 for a single job node i, of which more than one AGV is required for a delivery*

<u>Objective function:</u>

$$Min\ Z = \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} D_{ij} x_{ijk} \tag{1}$$

subject to

$$\sum_{j \in I} x_{kjk} = 1 \quad \forall k \in K \tag{2}$$

$$\sum_{j \in I} \sum_{k \in K} x_{ijk} \leq 1 \quad \forall k \in K \tag{3}$$

$$\sum_{k\in K} x_{ijk} \geq Q_{jl} - M(1-b_j) \quad \forall j,i \in J \text{ mit } Q_{jl} > 1 \tag{4}$$

$$\sum_{j\in J_Q} b_j \geq 1 \tag{5}$$

$$\sum_{i\in I} x_{ijk} \geq \sum_{h\in I} x_{jhk} \quad \forall j \in J, k \in K \tag{6}$$

$$\sum_{i\in S}\sum_{j\in S, j\neq i} x_{ijk} \leq |S| - 1 + \sum_{l\in(J\cup\{k\})\setminus S}\sum_{i\in S} x_{lik}\cdot(|S|-1) \quad \forall k \in K, S \subseteq J, |S| > 1 \tag{7}$$

$$\sum_{k\in K} x_{ijk} \geq Q_{ij} \quad \forall j \in J, i \neq j \text{ mit } Q_{ij} > 0 \tag{8}$$

$$\sum_{i\in K}\sum_{j\in J}\sum_{k\in K} x_{ijk} \geq \max_{i\in I, j\in I} Q_{ij} \tag{9}$$

The objective function (1) minimizes the distance travelled by the AGVs. Constraints (2) and (3) are start conditions for the AGVs. Constraint (2) ensures that each AGV starts from its own node, constraint (3) ensures that only one vehicle can start from each start node. Constraint (4) prevents a deadlock if there are several pick-up locations i that require more than one AGV for transportation. By means of constraint (5), it is ensured that the binary variable b becomes one for at least one pick-up location i where more than one AGV is required, so that a sufficient number of vehicles travel to the pick-up location. Constraint (6) ensures that at least as many AGVs enter each job node J as leave it. Subtours between the job nodes J are prevented by condition (7), as it needs to be ensured that each route contains at least as many start nodes as are required for the deliveries. Constraint (8) assigns the required number of vehicles to each delivery using the matrix $Q(i,j)$. Constraint (9) guarantees that the number of AGVs originating from the start nodes is sufficient to meet the maximum transportation requirements.

5 Solution of the Optimization Model and Determination of the Transport Order

5.1 Solution of the Optimization Model

The optimization model is implemented in the Python programming language using the PuLP library. Currently, the model is solved optimally for small model instances using the PULP_CBC_CMD solver integrated in PuLP. The decision variables x_{ijk}, which assume the value of one when a vehicle k travels from node i to node j, are output as the solution of the optimization model. These decision variables x_{ijk} are stored in a dictionary and returned. However, it is not immediately evident from the solution which order the transports are carried out and which vehicles are required to execute a delivery order together.

5.2 Determination of the Transport Order

A recursive method is employed to determine the transportation order based on the decision variables x_{ijk}. The recursive process is shown in Figure 2.

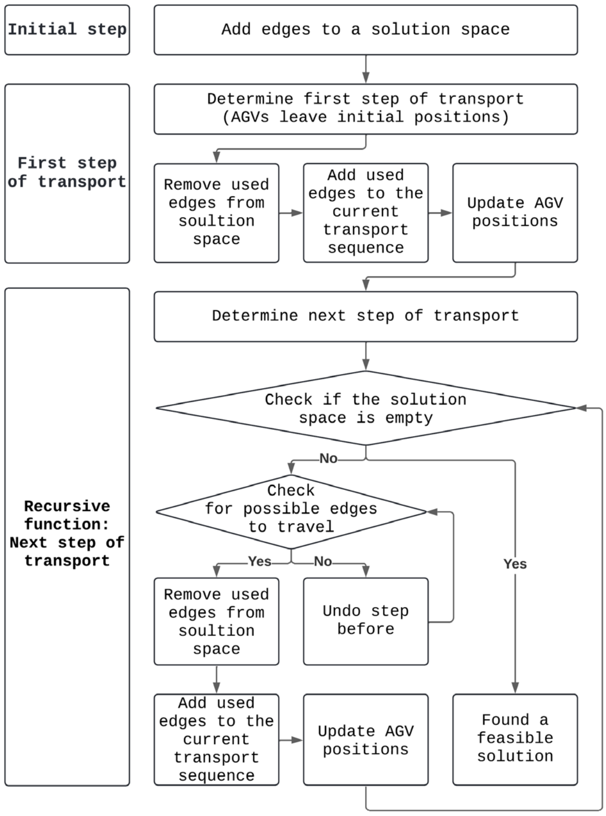

Figure 2. Schematic diagram for the recursive determination of the transport sequence

In a first step, all decision variables x_{ijk} with a value of one are added to a solution space. The first step of the transport is then determined. This consists of the AGVs leaving their start node and traveling to the first pick-up point. These edges are then removed from the solution space and the current transport sequence is saved in an *order_of_transport* dictionary. Additionally, the current position of the AGVs is updated by indicating the current job node.

The subsequent step is to determine whether any decision variables remain within the solution space. If this is not the case, it is possible to assign all decision variables to a transport step and subsequently determine a transport sequence. If decision variables remain in the solution space, the subsequent transport step is determined through an iterative process. To this end, the system initially determines which edges can be visited based on the current position of the AGVs and records them in a list designated *possible_edges*. The first entry in this list is then selected. Any edges that meet the first entry of this list are removed from the solution space and added as the next transport step in the dictionary of the current transport sequence. The current position of the AGVs is subsequently updated by specifying the new job nodes.

Based on the new positions, all possible edges that can be visited are determined again. If there are still edges available in the possible_edges list, the first entry is selected again, the transport sequence is updated, all edges matching this entry of the list are removed from the solution space, and the position of the AGVs is updated. If there are no edges available from the current position of the AGVs and there are still entries in the solution space, the last step is undone and the second entry is selected from the list of possible edges. These steps are performed recursively until there are no more decision variables in the solution space and thus a minimum distance transport order can be determined.

Figure 3 shows the transport order for the model environment of the example factory from section 3. First, all AGVs travel from the charging stations to node 7 to load a product that requires a total of six vehicles. This product is then delivered to node 8. AGVs 0 and 1 remain at this node. AGVs 2 to 5 travel to node 9 to load a product that requires a total of four vehicles and deliver it to node 10. AGVs 2, 3 and 5 then remain at node 10 and AGV 4 completes the remaining deliveries from node 11 to node 12 and from node 13 to node 6. This solution minimizes the total distance traveled by all AGVs when the model is solved once at the initial time and exactly one product is provided in each source.

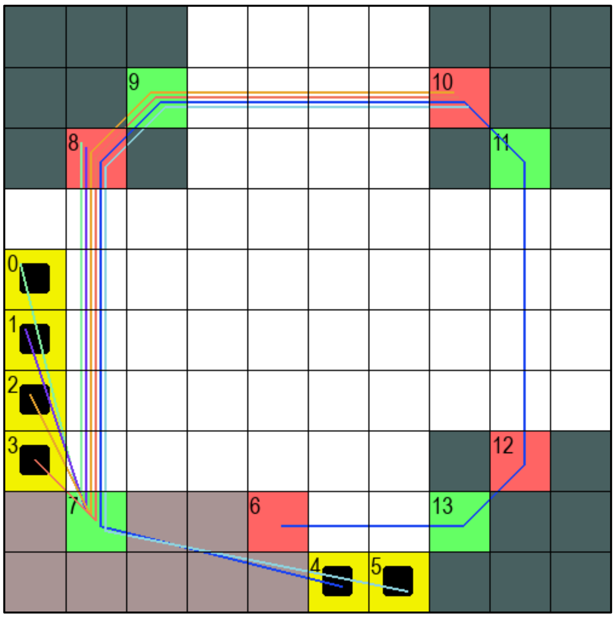

Figure 3. Visualization of the transport order for the example factory, the different colors of the paths represent the routes of the AGVs

5.3 DYNAMIC SOLUTION OF THE OPTIMIZATION PROBLEM IN A MODEL ENVIRONMENT

In order to ensure the ability to respond to changes in the transportation operations conducted within a dynamic factory, a methodology has been developed that enables the optimization model to be solved in an event-driven manner. The model is then recalculated in response to any changes that may have a relevant impact on the transportation process. The changes in question are as follows:

- A product is provided by a machine or a warehouse
- One or more AGVs unload a product at a machine or warehouse

The underlying concept is that, on the one hand, as soon as a product is provided by a machine or a warehouse, the upcoming transport request must be taken into account in the optimization model. On the other hand, AGVs that have unloaded a product are available again to carry out the next transport. In the dynamic case, only AGVs that are currently available are considered for the solution of the optimization model. This ultimately implies that, depending on the status of the factory, the optimization model can only be solved if there are sufficient vehicles available to accommodate all planned transports.

The dynamic solution of the optimization model also takes into account the state of a machine's input buffer. If the input buffer is full, the product designated for that machine is not included in the solution of the optimization model. This ensures that AGVs will always be able to unload transported products. This, together with the fact that only free AGVs are taken into account when solving the optimization model, ensures that no deadlocks or livelocks can occur.

Figure 4 shows exemplary transports that are carried out on the basis of the solution of the optimization model. The top left figure shows the transport with six AGVs from node 7 to node 8. The top right figure illustrates a transport involving four AGVs from node 9 to node 10. It can be observed that two AGVs remain at node 7, as they are not required for the aforementioned transport. The bottom left figure shows the transport with four vehicles from node 9 to node 10 and the transport with one vehicle from node 11 to node 12. The bottom right figure illustrates the transport with four vehicles from node 9 to node 10 and the transport with one vehicle from node 13 to node 6.

The dynamic solution differs from the static solution. Figure 3 shows for the static case that the AGV, which carries out the transports from node 11 to 12 and 13 to 6, is also involved in the transport from node 9 to 10 (see blue line). In the dynamic case, it is possible for a machine or warehouse to provide a product when AGVs are engaged in transportation. In such an instance, the nearest available

AGV is used to carry out the transport by solving the optimization model.

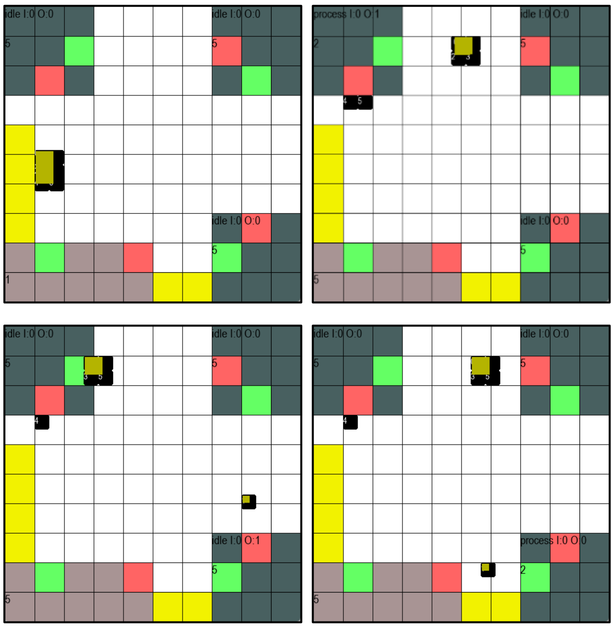

Figure 4. Transports carried out on the basis of the solution of the dynamic optimization model

6 EVALUATION OF LOGISTICAL TARGET VALUES

The evaluation of logistical target values is a crucial aspect of the process assessment. It should be noted that the factory used as an example in this publication is not a realistic representation of a typical factory. Rather, it is a factory that has been specifically constructed for the purpose of developing and testing the methods presented.

Currently recorded target variables are the workload of the machines, the workload of the AGVs and the stock of products in the system as well as the transport stock. The workload of the machines and the AGVs can be allocated to the logistics costs. The stock of products in the system and the transport stock are recorded in order to evaluate the logistics performance, which includes, among other things, the lead time of products. The following figures show the target variables for the example factory in a near steady state with product provision times of five seconds for the warehouse. The processing time for the machines is also five seconds.

Figure 5 shows the status of the three machines of the factory. It can be observed that all machines are operating at approximately 16 % capacity and are otherwise continuously idle. Only one machine is temporarily blocked following the initial initiation, as the remaining machines have not yet commenced production, and the first machine is therefore continuously supplied.

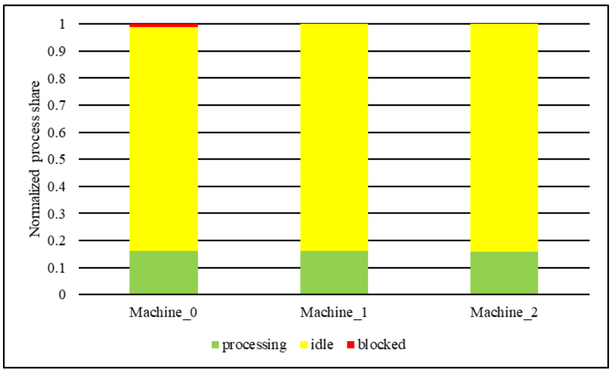

Figure 5. Workload of the machines

Figure 6 illustrates the workload of the AGVs. It can be observed that the distribution of workload among the vehicles is not balanced. Four of the vehicles exhibit an average workload utilization rate of approximately 32,4 %, while one AGV has a utilization rate of approximately 39,9 % and another AGV performs at a rate of approximately 18,2 %. This can be explained by the fact that in the steady state, the same AGV always carries out the transports from node 11 to 12 and 12 to 13 and another AGV, which is always the same, remains at node 7 while the other AGVs are engaged in other transport tasks. The average workload of the AGVs is 31,2 %.

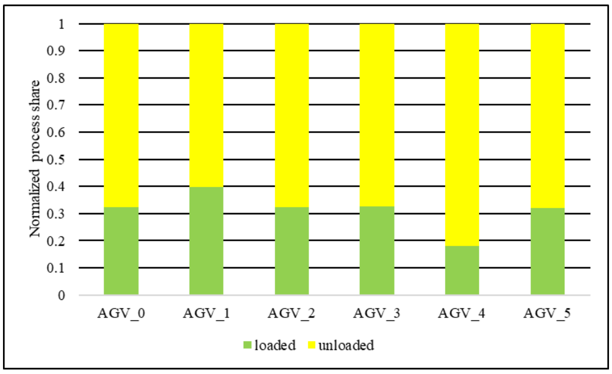

Figure 6. Workload of the AGVs

Figure 7 shows the average stock of products inside the factory during the simulation depending on the simulation step. It can be seen that the average system stock level settles at 2.61 products.

Figure 8 shows the average transport stock inside the factory during the simulation depending on the simulation step. It can be seen that the average transport stock level settles at 0.544 products.

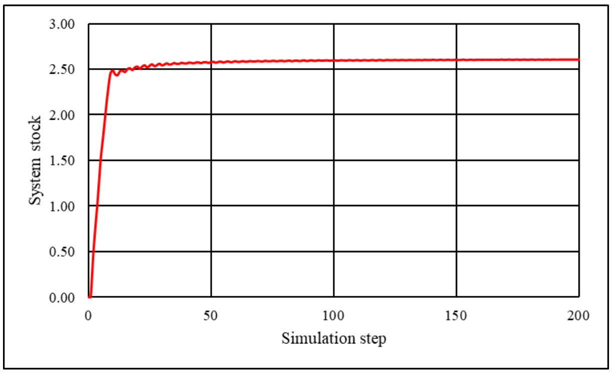

Figure 7. Average stock of products in the system as a function of the simulation step

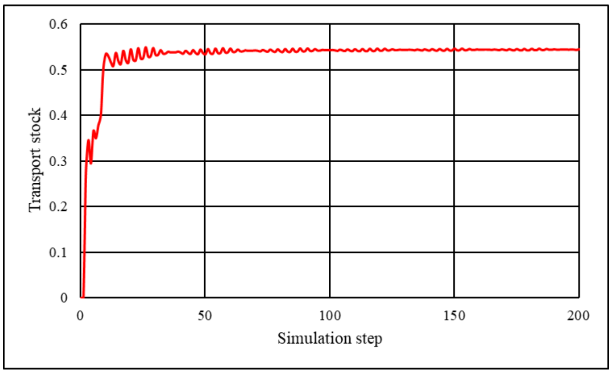

Figure 8. Average transport stock as a function of the simulation step

By employing the evaluation of logistical target values, it is possible to make a conclusion at a later date regarding the number of vehicles that are required for a specific application and the practical cases in which the use of cellular AGVs is beneficial [4].

Table 1 gives a first impression of how the number of AGVs affects the determined target values. It can be observed that the stock of products in the factory does not correlate with the number of AGVs and fluctuates. The transport stock appears to increase in accordance with an increase in the number of AGVs. An explanation for this observation can be that an increased number of vehicles in the system can effectively transport multiple products simultaneously. It can also be seen that an increased number of vehicles results in higher machine workload. The average machine workload rises from 16.1 % with six AGVs to 27.9 % with ten AGVs. An enlargement in the number of vehicles allows for a more rapid provision of products to the machines. The average utilization of the vehicles is nearly constant, regardless of the number of vehicles. Utilization is at least 29.2 % with a number of nine vehicles and 33.3 % with seven vehicles.

Table 1. Effects of the number of AGVs on the selected logistical target values

		6 AGVs	**7 AGVs**	**8 AGVs**	**9 AGVs**	**10 AGVs**
Average Stock	**System**	2.61	3.23	2.42	2.33	3.68
	Transport	0.544	0.674	0.747	0.763	0.938
Workload	**Machine_0**	0.162	0.202	0.224	0.228	0.282
	Machine_1	0.161	0.197	0.221	0.225	0.279
	Machine_2	0.160	0.197	0.221	0.221	0.276
	AGV 0	0.324	0.403	0.303	0.273	0.293
	AGV 1	0.399	0.342	0.256	0.243	0.285
	AGV 2	0.324	0.341	0.298	0.208	0.292
	AGV 3	0.324	0.403	0.379	0.306	0.296
	AGV 4	0.182	0.400	0.308	0.381	0.336
	AGV 5	0.324	0.225	0.314	0.264	0.360
	AGV 6		0.219	0.349	0.313	0.360
	AGV 7			0.371	0.311	0.377
	AGV 8				0.331	0.315
	AGV 9					0.331

7 Conclusion

With the help of the presented optimization model, it is possible to optimize the transport of products in a factory environment with cellular AGVs under the objective of minimizing transport distances. Using the recursive method introduced, the solution of the optimization model can also be used to determine a transport sequence that satisfies the condition of the shortest transport distance and simultaneous, collaborative transport with multiple AGVs. The provided model environment also allows the optimization model to dynamically respond to changes in a factory. On this basis, logistical target values can be evaluated to assess cellular transportation.

In order to be able to solve larger model instances, a heuristic will be developed in the future, which will allow to solve the optimization model in a short time. In addition, the model environment and the optimization model are extended with additional constraints to represent realistic use cases. Possible constraints are charging states of the AGVs and driving on defined paths in the model environment. For realistic use cases, the factory environments are also implemented using standard 3D simulation software Finally, an evaluation of economic and logistic target variables in comparison to conventional means of transport is planned in order to be able to evaluate transport with cellular AGVs.

8 Funding

This article is published as part of the research project "Development of a heuristic model approach to investigate the efficiency of cellular FTF in intralogistics " funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) with the funding code 505849793.

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Torben Mente, M.Sc., Project Engineer, IPH – Institut für Integrierte Produktion Hannover gGmbH

Torben Mente was born 1993 in Celle, Germany. Between 2011 and 2017 he studied industrial engineering at Leibniz Universität Hannover, specializing in production technology and production management. Since 2021, he has been working at IPH in the Production Automation department.

Address: IPH – Institut für Integrierte Produktion Hannover gGmbH, Hollerithalle 6, 30419 Hannover, Germany, Phone: +49 511 27976-236, Fax: +49 511 27976-888, E-Mail: mente@iph-hannover.de

Dr.-Ing. Benjamin Küster., Head of Production Automation Department, IPH – Institut für Integrierte Produktion Hannover gGmbH

Dr.-Ing. Benjamin Küster (*1988) studied industrial engineering at Leibniz Universität Hannover, specializing in production engineering and business informatics. He has been working as a project engineer in the field of production automation since November 2014. He has been Head of Production Automation since September 2017.

Dr.-Ing. Malte Stonis, Coordinating Managing Director, IPH – Institut für Integrierte Produktion Hannover gGmbH

Dr.-Ing. Malte Stonis (*1979) studied mechanical engineering at Leibniz Universität Hannover, specializing in vehicle systems and biomedical engineering. He has worked at IPH since 2006, initially as a project engineer in the Process Technology department and from 2008 as head of department. Malte Stonis has been Coordinating Managing Director of IPH since September 2016.

Prof. Dr.-Ing. Ludger Overmeyer, Managing Director, IPH – Institut für Integrierte Produktion Hannover gGmbH, Head of Institute of Transport and Automation Technology (ITA), Leibniz University Hannover

Prof. Dr.-Ing. Ludger Overmeyer, born in 1964, studied electrical engineering at the University of Hanover and then worked as a research assistant at the Laser Zentrum Hannover e.V. (LZH). After obtaining his doctorate in engineering, he worked as a manager in the field of research and development in mechanical and plant engineering for the semiconductor industry. Since 2002, he has headed the ITA at Leibniz University Hannover. In 2007, he took on the role of managing partner of IPH.

Address: Institut für Transport- und Automatisierungstechnik, Leibniz Universität Hannover, An der Universität 2, 30823 Garbsen, Germany

Prof. Dr.-Ing. habil. Peter Nyhuis, Managing Director, IPH – Institut für Integrierte Produktion Hannover gGmbH, Head of Institute of Production Systems and Logistics (IFA), Leibniz University Hannover

Prof. Dr.-Ing. habil. Peter Nyhuis, (*1957), studied mechanical engineering at the Leibniz Universität Hannover and, subsequently, worked as research associate at the Institute of Production Systems and Logistics (IFA). After receiving his doctorate in mechanical engineering he habilitated before he became executive manager in the field of supply chain management for the electronic and mechanical engineering industry. Since 2003 he has been heading the Institute of Production Systems and Logistics (IFA) at the Leibniz Universität Hannover. In 2008, he became member of the management board of the IPH.

Address: Institut für Fabrikanlagen und Logistik, Leibniz Universität Hannover, An der Universität 2, 30823 Garbsen, Germany

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