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Machine Learning and Digital Twin-Based Path Planning for AGVs at Automated Container Terminals

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Abstract. The complex and dynamic environment in an automated container terminal (ACT) increases the difficulty of path planning, especially for automated guided vehicles (AGVs). Digital twin is an essential means of characterizing complex production systems as the physical objects can be synchronized in the virtual space. Machine learning is also a popular way to solve path planning problems. This study combines digital twin and machine learning to tackle AGV path planning problems in the time-changing operation environment. A digital twin-based AGV scheduling approach is developed to obtain the real-time data from the physical ACT. Based on the information of the dynamic factors obtained, a mathematical model is formulated to minimize the transportation time of AGVs. Subsequently, the path planning schemes solved by machine learning are used asinput to the virtual ACT for validation and optimization. The optimized solution is further compared to a common path plan algorithm without applying digital twin. The experimental results show the superiority of the proposed method, which can provide better decision support for ACT operation.

Keywords. Automated guided vehicle, path planning, digital twin, machine learning, decision support

Introduction

Automated guided vehicle (AGV) is one of the equipment for horizontal transportation at automated container terminals. Normally, AGV is responsible for delivering containers between the storage yard and the quay side. There are some uncertain factors that will affect the operation of AGVs at an automated container terminal. For example, equipment failure, bad weather and other unknown events are not prevised in the dynamic operation environment. These uncertain events may disturb the current path plan of AGVs when one or more of them occurs unexpectedly. Digital twin is an important mean of delineating and simulating complex systems to achieve optimization [1]. By digital twin, the physical and virtual world can be built to reflect aspects of production process which are driven by data from the real environment. As the dynamic operating process of the physical world can be monitored in real time through digital

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twin, the uncertain factors can be detected with the simulation of the virtual world. Then some actions can be taken to respond to the uncertain factors occurred in the actual operation, such as adjusting the current production plan and rescheduling the operating process. A job shop scheduling method based on digital twin [2] was proposed to reduce the bias caused by uncertain events or abnormal disturbances in the scheduling process. Therefore, digital twin provides a new way of addressing uncertain factors in production scheduling.

This paper proposes a digital twin-based approach for AGV path planning to deal with uncertain factors in the complex and dynamic environment. The horizontal transportation of AGV involves multiple operation processes at the automated container terminal. The containers are delivered from the storage yard to quay cranes by AGVs, and then are loaded onto vessels. There are many container blocks for storage and many quay cranes for loading, which brings about many path choices for transporting. During the transportation, some uncertain factors may disturb the path planning of AGVs. With the support of digital twin, the operating condition at the container terminal can be monitored in real time and be mapped in the virtual models. Then, a machine learning method is combined with digital twin to plan the path for AGVs. Based on the interaction of physical and virtual spaces in the digital twin, it responds to the disturbance in the physical space. Machine learning method such as Q-learning is applied to adjust and update the path planning for adapting current operation.

The novelty of this paper is to apply digital twin and machine learning method into the operation research. The AGV path planning can be described to be a mixed integer programming model which was solved with operation research approach traditionally. In this paper, dynamic information of AGV operation is obtained to plan the path with the application of digital twin. Based on the real-time task data, AGV path evaluation is implemented by machine learning. The AGV path planning schemes are input to the virtual container terminal for verification until the optimization goal is achieved.

The remainder of this paper is organized as follows. In Section 1, the related work on AGV path planning and digital twin is summarized. In Section 2, path planning problem for AGVs at an automated container terminal is described and the mixed integer programming problem is formulated. The solution approach based on digital twin and machine learning is designed in Section 3 and the case studies are analyzed in Section 4. Section 5 provides the conclusions and further research.

1. Related work

This section summarizes the literature related to AGV path planning and digital twin. As for path planning, it involves finding an optimal path for vehicles to spend the least time or the shortest distances on transporting. Hamed et al. [3] considered the lead time and delay time of tasks when planning path for AGV, and then obtained the ideal solution by solving the minimum penalty function. Errico et al. [4] established path planning models for random service time in the hard time window and applied the branch and bound method to address AGV path planning problem. Nishi et al. [5] proposed a distributed path planning method for multi-AGV by establishing the probability distribution function of collision which was caused by the delay during the AGV movement. They found the optimal paths of multi-AGV through simulation in a dynamic transportation environment.

To address conflicts on AGV path, some research proposed the control strategies and machine learning methods. Choe et al. [6] proposed an online preference learning algorithm to dynamically adjust the operation strategy of AGV. They applied artificial neural network to realize the learning of preference function and analyzed the adaptive scheduling scheme of AGV by simulating different strategies. Zhou et al. [7] proposed a real-time scheduling method based on Q-learning, which optimized the operation plan through learning path selections of AGV in real-time state. Miyamoto et al. [8] developed local and random search algorithms to achieve conflict-free path planning for AGVs when considering vehicle capacity and buffer constraints. Xin et al. [9] simulated static and dynamic obstacles of AGVs based on the overall graph sequence, and then proposed a collision-free scheduling algorithm in a hierarchical control architecture to generate collision-free paths for AGVs. Fanti et al. [10] proposed a decentralized control-based coordination algorithm that first assigns tasks to AGVs through a consensus-based approach, and then schedules AGVs to move in a proposed path network based on a regional control strategy, avoiding collisions and deadlock-free behavior. To find the shortest path and avoid the conflicts of AGVs, Hu et al.[11] studied a multi-agent reinforcement learning method which scored and learned the selection of paths.

Digital twin was first proposed by Grieves and Vickers [12], which was helpful to reflect the actual operation in real time and provide guidance for the production decision. A virtual model of physical entities was created to simulate and reflect their state and behavior through modeling and simulation, and predict their future state based on real-time data, which show that models and data are the core elements of digital twin [13]. Many studies investigated into digital twin applications on decision-making, such as production operation and scheduling optimization.

In the smart factory, Wang and Luo [14] proposed a digital twin framework and built a virtual space for the full life cycle of a product. Then the results solved by a big data learning and analysis model were verified iteratively in virtual space to provide decision support for production. The digital twin model of autonomous vehicles was established for obtaining a better design, in which the physical entity-based model can collect information with virtual entities to provide correlation analysis in the data service module [15]. Digital twin makes it possible to develop more flexible and adaptable products in a rapidly changing and complex world, as it can learn and adapt relevant behaviors based on feedback from the physical world [16]. Wang et al. [17] proposed a digital twin design framework in manufacturing systems which realized real-time monitoring, work order scheduling and other functions through digital twin intelligent modules. To respond to changes of market demand in a timely manner, Liu et al. [18] proposed an intelligent workshop scheduling method based on digital twin and proved its effectiveness by comparing with traditional genetic algorithms.

Considering the uncertainty and equipment failures of real-time detection in workshop production, a workshop scheduling framework based on digital twin was proposed [19], which mainly included an optimization module and a digital twin module. The operation sequence was simulated by using real-time data from industrial equipment in the workshop to achieve synchronization with the real operation scene. Meanwhile, the data-driven analysis function integrated in the digital twin was applied to deal with the uncertainty and to calculate the failure probability of the equipment based on the real-time data. The genetic algorithm and the simulation model were combined in the optimization module to formulate an optimal workshop scheduling. As for the uncertain factors in workshop scheduling, Wang et al. [20] also proposed a planning and scheduling system based on digital twin. Before production, the uncertain factors in the production process were processed in advance through data prediction and simulation verification to make an initial production plan. During the production, the uncertainty factors were monitored through the consistency comparison between simulation and real-time data. According to the uncertain factors found in time, the production plan was adjusted again to ensure its feasibility. To address the interfere of multi-crane, a digital twin-driven multi-crane scheduling method was adopted to integrate the virtual cranes with the physical cranes [21]. The dynamic behaviors of the physical multi-crane system were simulated in the virtual models, and the energy consumption of different multi-crane scheduling schemes were pre-assessed. Then the feasibility and effectiveness of multi-crane scheduling were to be improved based on the evaluation results.

The literature on AGV path planning mostly focused on solving the conflict-free paths with heuristic algorithms. More research tends to use machine learning methods as the complexity of the path environment which have a better solution. In addition, digital twin provides the new mode for optimization in the production scheduling system as it can deal with the dynamic environment by real-time monitoring and responding. Faced with the uncertain factors, this paper applies digital twin to reflect the operation condition at automated container terminals and combines machine learning method to plan paths for AGVs.

2. Problem statement and model fomulation

2.1. Problem statement

The problem studied in this paper relates to the container transportation at the automated container terminal. The loading and unloading operation of the container vessels involves the movement of containers through the automated container terminal. The import containers unloaded from the vessel are transported to the storage yard. In turn, the export containers are transported from the storage yard and loaded onto the vessel. The loading and unloading equipment of vessels are quay cranes, while the loading and unloading of the storage yard occurs in the exchange area. The container is handled by yard cranes from the storage location to the exchange area which is set at the sea side of the container block. It needs AGVs to transport containers between quay cranes and container blocks. The layout of container transportation is provided in Figure 1.

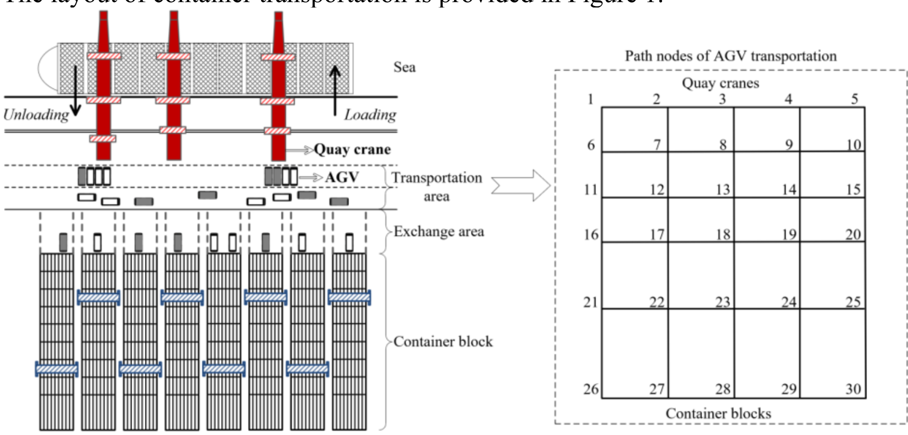

Figure 1. Layout of AGV transportation at container terminal.

To meet the requirement of loading containers on vessels, all containers are asked to be delivered to quay cranes within the given time before the vessel leaves the terminal. The loading efficiency of vessels depends on the transportation jobs as the quay crane can only load the arrived containers. Containers should be transported to quay cranes in a reasonable way to shorten the loading time of vessel.

The transportation of containers can be described as a sequence of tasks between container blocks and quay cranes. To complete all tasks, the path planning of AGVs can be decomposed into two parts. The first is to choose the destination of the AGV, meaning that the container is transported to which quay crane. The second is to decide the transporting path as there are many path choices for AGV from the container block and the quay crane.

The problem addressed above focuses on the path optimization of AGVs with the objective of minimizing the transporting time for all tasks. It is assumed that the operation information of tasks has been known including the storage location of containers. The battery capacity of AGV is enough to support the transportation and recharging of AGVs is not considered in this study.

2.2. Model formulation

Based on the problem statement, a mathematical model is formulated which includes notation definitions, objective function, and related constraints. The notation definition of the model is shown in Table 1.

Table 1. Definitions of notations in the model.

Notations	Definitions
n	Index of tasks
k	Index of AGVs
s	Index of path steps
i, j	Index of path nodes
N	Sets of tasks
K	Sets of AGVs
D	Sets of path nodes
S_n	Passing path steps of task n
p_{ij}	The length of the path formulated by node i, j
$c_{nkp_{ij}}$	Number of waiting when AGV k transports task n on path p_{ij}
v, v_0	Speed of AGV
a	Acceleration of AGV
d	Safe driving distance of AGV
$t_{nkp_{ij}}$	Waiting time when AGV k transports task n on path p_{ij}
x_{nk}	$x_{nk} = 1$ means that AGV k transports task n
y_{kis}	$y_{kis} = 1$ means that AGV k choose node i at step s

$$\min f = \sum_{n \in N} \sum_{k \in K} \sum_{p_{ij} \in P} x_{nk} \cdot \left(y_{kj(s+1)} - y_{kis} \right) \cdot \left(\frac{p_{ij}}{v} + t_{nkp_{ij}} \right) \tag{1}$$

$$\sum_{k \in K} x_{nk} = 1, \forall n \in N \tag{2}$$

$$\sum_{i \in D} y_{kis} = 1, \forall k \in K, s \in S \tag{3}$$

$$\sum_{j \in D} y_{kj(s+1)} = 1, \forall k \in K, s \in S \tag{4}$$

$$\sum_{k \in K} y_{kis} \leq 1, \forall i \in D, s \in S \tag{5}$$

$$\sum_{k \in K} y_{kj(s+1)} \leq 1, \forall j \in D, s \in S \tag{6}$$

$$\sum_{i \in D} y_{kis} = y_{kj(s+1)}, \forall k \in K, j \in D, s \in S \tag{7}$$

$$y_{kis} \leq \sum_{j \in D} y_{kj(s+1)}, \forall k \in K, i \in D, s \in S \tag{8}$$

$$S_n \cdot x_{nk} = \sum_{s \in S_n} y_{kis}, \forall k \in K, n \in N, i \in D \tag{9}$$

$$t_{nkp_{ij}} = 2 \cdot c_{nkp_{ij}} \cdot \left(\frac{v - v_0}{a} - \frac{d}{v} \right) \tag{10}$$

$$x_{nk} \in \{0,1\}, \forall n \in N, k \in K \tag{11}$$

$$y_{kis}, y_{kj(s+1)}, \in \{0,1\}, \forall k \in K, i, j \in D, s \in S_n \tag{12}$$

Objective (1) is to minimize the transporting time for all tasks, which is composed of the transportation time and waiting time on paths. The AGV passes the nodes i and j at two continuous steps, and its transportation time depends on the path length and driving speed.

As one task can only be transported once and AGV has its own driving rules, the following equations are provided. Constraint (2) guarantees that there is one and only one AGV being assigned to one task. Constraints (3) and (4) guarantee that there is one and only one path node for AGV at one step. Constraints (5) and (6) mean that one path node can only pass one AGV at one step. Constraints (7) and (8) ensure that one AGV chooses only one path node at one step and AGV only drives to the next path node after passing the current node.

Constraint (9) ensures the number of path nodes for the task, that is, AGV completes all path steps required by the task. Constraint (10) shows that the decelerating and accelerating time of AGV when meeting conflicts. Constraints (11) and (12) are the integer restrictions of the decision variables.

3. Approach design

The solution approach used in this paper combines digital twin and Q-learning to carry out the path planning of AGVs. As illustrated in Figure 2, the operation of container transportation is monitored through the automated container terminal digital twin system. The stored container blocks and the destinated quay cranes of tasks are provided for AGVs to transport. In addition, the dynamic changes during the operation are grasped to being considered for path planning, especially occurring conflicts on transportation. With the support of digital twin, task information and operation condition are obtained at the automated container terminal. Q-learning is applied to learn the path choices of transportation tasks. The optimal paths with the minimum transporting time are planned for AGVs by Q-learning.

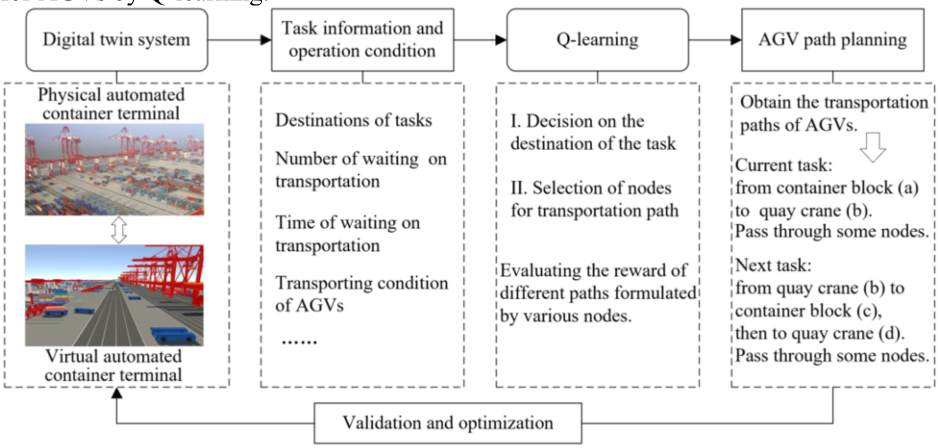

Figure 2. Digital twin-based Q-learning for AGV path planning.

The developed automated container terminal digital twin system helps to observe and collect the real-time operation data from the physical space as reported in Gao et al. [22]. Then, the information of transportation tasks and AGV operation is input to Q-learning for deciding the destinations and paths. Based on the formulated mathematical model, the transporting time depends on the path distances and waiting time of AGVs. The related data is obtained from the physical automated container terminal and the wait caused by conflicts is prevised from the virtual automated container terminal. As the physical and virtual spaces keep synchronize in digital twin, the dynamic operating environment of the automated container terminal is monitored in real time. The instant information determines the parameters of the model for AGV path planning in the proposed approach.

Q-learning method calculates the reward by the bellman equation, as shown in (13). Q-learning updates the Q value for the state and the action of the AGV, where $Q^{new}(s,a)$, $Q(s,a)$ represents the new Q value and the current Q value. At a new state, all possible actions are given reward and the maximum expected future reward is represented by $\max Q(s^{'},a^{'})$. The reward that AGV chooses an action at a state is described with $R(s,a)$. The parameters α,γ represent the learning rate and discount rate respectively, which determine the action learning and the state value.

$$Q^{new}(s,a)=Q(s,a)+\alpha\cdot(R(s,a)+\gamma\cdot\max Q(s^{'},a^{'})-Q(s,a)) \tag{13}$$

To ensure that AGVs transport all task with the least time, there is a need to evaluate all possible paths for AGV choosing an optimal transportation path. Q-learning achieves the evaluation of different paths chosen by AGV at various states. In the transportation network, an AGV assigned to a task starts from a starting node and it has two or more node selections for the next step. There are multiple transportation paths for one task, and then AGV needs to choose an optimal path plan. As for the task transported by AGV, the node choice of each step is rewarded, and the total reward of all choices required by the task is compared to obtain the best value.

Based on digital twin, real-time information required for AGV transporting tasks is transmitted to Q-learning to decide the task destinations and transportation paths. Meanwhile, the path plan solved with Q-learning is input to the virtual automated container terminal to verify and optimize the solution. Then, the final path plan of AGVs is conducted in the physical automated container terminal to transport containers. The path planning includes that AGV assigned to the current task transports from the container block to quay crane passing the selected nodes, and transports from the current quay crane to the container block of the next task passing other selected nodes.

4. Case analysis

The experimental examples are conducted to verify the proposed digital twin-based Q-learning approach. The small-size experiments are performed with Gurobi and digital twin-based Q-learning, which is used as a benchmark comparison. The solution results of small-size cases are presented in Table 2. The proposed approach is effective by comparing the total transporting time solved with two methods. The solution is better than that of Gurobi and the solution gap between them is larger as the task size becomes bigger. The difference of transporting time is only 12.9 seconds when there are ten container tasks. It also signifies that the proposed approach can obtain effective solutions.

Table 2. Solution results of small-size cases.

Task size	Total transporting time (seconds)		
	Gurobi	The proposed approach	Gap
10	260.2	247.3	5.22%
20	601.6	568.3	5.86%
30	1111.8	1001	11.0%

Table 3 presents the transportation paths of ten tasks which are solved with the digital twin-based Q-learning. Containers are stored in different container blocks which are transported respectively from the nodes [26, 27, 29, 30]. Their destinations are near the nodes [2, 4, 5], and then AGVs complete transportation tasks according to the selected paths.

Table 3. The path plan of ten tasks obtained from the proposed approach.

Task number	Passing nodes
1	[30, 25, 20, 15, 10, 5]
2	[29, 24, 19, 14, 9, 4]
3	[27, 22, 17, 12, 7, 2]
4	[26, 21, 16, 11, 12, 13, 8, 3, 4]
5	[29, 28, 27, 22, 17, 12, 7, 2]
6	[27, 26, 21, 16, 11, 12, 13, 8, 9, 4]
7	[27, 22, 17, 12, 7, 2, 3, 4]
8	[27, 22, 17, 18, 13, 8, 3, 4]
9	[26, 21, 22, 23, 24, 19, 14, 9, 4]
10	[29, 24, 19, 14, 9, 4]

To illustrate the superior performance of the proposed digital twin-based Q-learning approach, three sizes of cases are used to compare with the Dijkstra algorithm. Dijkstra is a common algorithm for solving path planning problems. The solution results obtained from the two approaches are provided in Table 4. It can be found that the solution of the proposed approach is superior to that of the Dijkstra algorithm and the solution gap becomes larger as the number of tasks becomes more. The proposed approach uses digital twin to obtain the real-time information and verify the path planning from Q-learning, which can grasp and deal with the uncertain factors in the dynamic operating environment. Then, the paths of AGVs solved with digital twin-based Q-learning approach need less transporting time than that of the Dijkstra.

Table 4. Comparison results of two approaches.

Task size	Total transporting time (seconds)		
	Dijkstra algorithm	**The proposed approach**	**Gap**
50	2167.4	2033.1	6.61%
100	6980.5	6501.8	7.36%
150	13070.1	11831.3	10.47%

By comparing the solution results of the above three methods, the gap of 100 tasks is less than that of 30 tasks, which shows that the performance of the Dijkstra is better than Gurobi. Overall, the solution performance of the proposed approach is the best in any size problems. This indicates that the proposed approach can effectively solve the path planning of AGVs even when the problem scale becomes larger.

5. Conclusions

In this study, the AGV path planning problem in the automated container terminal is proposed and solved by combining digital twin and machine learning method. A mathematical model for AGV path planning is formulated to minimize the transporting time and solved with Gurobi in small-size cases. The numerical results are compared with the solutions obtained from the digital twin-based Q-learning which verifies the effectiveness. Large-size cases are also performed with two algorithms to demonstrate the superiority of the proposed approach. The case analysis shows that the larger the task scale, the more obvious the performance advantage of the solutions from digital twin-based Q-learning than that of Dijkstra algorithm. An integrated dispatching of AGVs and other associated equipment during the automated container terminal operation can be further studied to provide decision support for operators.

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Statement of originality

The authors declare that this paper is original and that no sources other than those mentioned in the paper and its references have been used in creating it.

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