Scheduling Problems of Automated Guided Vehicles in Automated Container Terminals Using a Genetic Algorithm

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Abstract. The automated guided vehicle (AGV) is adopted as horizontal transport equipment in automated container terminals. In order to improve the operation efficiency of the AGV, we constructed a mixed integer programming model for AGV scheduling optimization in unloading operations in an automated container terminal with a vertical layout. The model aimed at minimizing the end time of the last task and the time of AGV invalid operation. The constraints included the operation limit and the time window. We also designed a genetic algorithm to solve the model, and set three experiments to prove the superiority of the method. The experimental results show that the genetic algorithm can significantly improve the calculation efficiency in large-scale AGV scheduling problem, and the scheduling model we constructed can better improve the operation efficiency of the AGV. We also simply studied the problem of the optimal number of AGV configurations.

Keywords: Automated guide vehicle (AGV); Scheduling; Genetic algorithm; Automated container terminals.

1. Introduction

Operations of automated container terminals include quay crane operations, yard crane operations, and horizontal transportation operations. The automated guided vehicle (AGV) is the main equipment for horizontal transportation in automated container terminals. The operation efficiency of the AGV directly affects the overall operation efficiency of the terminal. Because of multiple factors such as rising labor costs, large-scale development of ships and terminal operation automation, the terminal operation efficiency has been increasingly valued by terminal managers and shipping companies. Therefore, how to optimize the scheduling scheme to improve the operation efficiency of AGV has become a hot issue to be discussed, for which can improve the terminal operation efficiency and reduce the terminal operation cost.

Many scholars have conducted in-depth research on the AGV scheduling problem. Y. Xing et al. established a mixed integer linear programming (MILP) model with the goal of minimizing the total delay of quay cranes, and adopted two heuristic methods to assign AGVs to quay cranes [1]. A. Gudelj et al. optimized the shortest time and minimum number of AGV transport based on Petri nets by a genetic algorithm (GA), and presented a matrix-based formalization method [2]. P. Angeloudis et al. studied AGV scheduling of terminals under uncertain conditions, and proposed a more effective heuristic algorithm and alternative algorithm [3]. Fazlollahtabar et al. designed a two-stage optimization algorithm aiming at minimizing the early arrival and late arrival of the AGV, and proposed that MILP
can be used to solve small-scale problems while heuristic algorithms to solve large-scale problems [4]. Y. H. Ma et al. considered the uncertain environment such as traffic control and traffic congestion in the container yard, and pointed out the specific impact of uncertain factors and the number of AGV configurations on operation efficiency [5]. K. G. Huo et al. proposed a MILP model of multi-load AGV scheduling aiming at minimizing the total operating cost [6]. Homayouni et al. used a genetic algorithm to solve the comprehensive optimization problem of quay cranes, vehicles, and storage platforms for automated container terminals [7]. Luo et al. studied container storage and vehicle planning issues and proposes a dual-loop strategy to solve the problem [8].

Many scholars have studied the scheduling problems of the AGV from various angles, aiming at optimizing the operation process in the actual production of terminals. However, current research still has some problems such as inaccurate model establishment or slow algorithm convergence, so it does make sense to continuously improve the model and design a better algorithm, so as to optimize the scheduling system and improve operation efficiency. And this is also the starting point of this paper.

2. Problem Statement

Figure 1 shows an automated container terminal with a vertical layout. When unloading the ship, the quay crane (QC) reaches the designated position according to operation instructions. The main dolly of the quay crane obtains the container from the designated position of the ship, and places it on the transit platform. After the AGV reaches the quayside, the gantry dolly suspends the container to the AGV. And then the AGV follows the specified path to the designated container yard area, unloads the container on the bracket of the yard buffer area by its lifting platform, and then drives away to prepare for the next task.

![Figure 1. An automated container terminal with a vertical layout.](image)

After receiving the task instruction, each AGV immediately departs from the docking station, reaches the designated quayside to load a container, and travels to the designated container yard to complete the task. Then, the no-load AGV select the next task based on the optimization rules and drives to that quayside. The AGV will repeat the above process until all tasks are completed, and then return to the docking station. Upon completion of a task, the AGV will immediately check whether there are any tasks waiting to be executed, and execute them if so. Otherwise, the AGV will return to the docking station and finish the scheduling.

3. Model Building

3.1. Assumption

The establishment of the model is based on the following conditions:

- The unloading sequence of containers is known, and quay cranes can perform unloading operations strictly according to the determined sequence.
- The positions of quay cranes and container yards are known, and one quay crane corresponds to multiple container yards.
- Each yard crane is equipped with a buffer area, and the storage capacity of the buffer area and the speed of the track crane can meet the transport speed, so the impact of the yard crane will not be considered.
The quay cranes, AGVs and yard cranes will not fail. The AGVs can travel smoothly, so traffic jam, obstacle avoidance, conflict or other problems of AGVs will not be considered.

3.2. Model
In order to improve the AGV operating efficiency in terminals, we construct a mixed integer programming model, aiming to minimize the end time of the last task and the time of AGV invalid operations. We set the notations as follows: \( I \) is the set of tasks, and \( i,j \) are the sequence numbers of tasks. \( K \) is the set of AGVs, and \( k \) is the number of the AGVs. \( x_{i,j,k} \) is a 0/1 decision variable. If AGV-\( k \) executes the next task \( j \) immediately after completing task-\( i \), then \( x_{i,j,k}=1 \), otherwise \( x_{i,j,k}=0 \). The objective function of the model is as follows:

\[
F(x) = \min \left[ \max(z_{i,k} + t_{i,k}) + \frac{\lambda}{\mu} \sum_{i,j,k} x_{i,j,k} t_{i,j,k} \right]
\]

It consists of two parts. The first part is to minimize the end time of the last task, that is, the maximum of the start time \( z_{i,k} \) and the task execution time \( t_{i,k} \) executed by AGV-\( k \). \( z_{i,k} \) is equal to the sum of the start time of the previous task \( i' \) and the execution time of task-\( i \), and \( z_{i,k} \) also should be greater than the minimum time \( A_i \) at which the first task can be started:

\[
z_{i,k} = \max [(z_{i,k} + t_{i,k}), A_i]
\]

And the task execution time \( t_{i,k} \) is the sum of the transportation time \( t_{f,i,j,k} \) and the invalid operation time \( t_{l,i,j,k} \) of AGV-\( k \).

The second part deals with the total invalid operation time \( g(x) \) of AGVs by using the exponential penalty function \( G(x) \) in (3). Total invalid operation time \( g(x) \) of AGVs includes no-load time and waiting time under quay cranes in (4).

\[
G(x) = \frac{1}{\mu} \sum_{i=1}^{\lambda} e^{\mu t_{i,k}(x)}
\]

\[
g(x) = \sum_{i,k,j,l} x_{i,j,k} (t_{f,i,j,k} + t_{w,i,j,k})
\]

The constraints of the model are as follows:

\[
\sum_{j \in \{d(k)\}} x_{i,j,k,l} = 1, \forall k \in K
\]

\[
\sum_{i \in \{o(k)\}} x_{i,j,k,l} = 1, \forall k \in K
\]

\[
\sum_{i \in \{d(k)\}} x_{i,j,k} - \sum_{i \in \{o(k)\}} x_{i,j,k} = 1, \forall k \in K, j \in I
\]

\[
\sum_{i \in \{d(k)\}} x_{i,j,k} = 1, \forall i \in I
\]

\[
x_{i,j,k} + x_{j,i,k} \leq 1, \forall i,j \in I, i \neq j, \forall k \in K
\]

\[
z_{i,k} \geq A_i \forall i \in I, \forall k \in K
\]
\[ x_{i,j,k}(z_{i,k} + t_{i,j,k} - z_{j,k}) \leq 0, \forall i, j \in I, \forall k \in K \]  

(11)

\[ tw_{i,k} \leq 2ts, \forall i \in I, \forall k \in K \]  

(12)

\[ z_{j,k} - A_i \leq 2ts, \forall i \in I, \forall k \in K \]  

(13)

Equations (2) to (4) describe the AGV driving network structure that the AGV must start the transport at the virtual starting point \( o(k) \), and drive to the virtual ending point \( d(k) \) after completing all tasks. It must be ensured that the in-degree of each endpoint is equal to the out-degree. Equation (5) constraints that each task can be performed by one AGV only. Formula (6) constraints that the start and end of the same task must be executed by the same AGV. Formula (7) constrains that the start time of each task should be no less than the minimum time required for the quay crane to unload containers. Formula (8) constrains the time of the AGV that if AGV-\( k \) executes task \( j \) after completing task-\( i \), then the time point at which it starts to execute task \( j \) should be no less than the sum of the time \( z_{i,k} \) of starting to execute task-\( i \), the wait time \( tw_{i,k} \) on the quayside, and the travel time \( t_{i,j,k} \) from the execution point of task \( i \) to task \( j \). Formula (9) constrains the number of AGVs waiting on the quayside to no more than two pieces. Formula (10) constrains the number of containers waiting to be unloaded on the quay crane buffer to no more than two TEUs.

4. Genetic Algorithm

AGV scheduling problem is an NP-hard problem, which cannot be solved by exact algorithms. Considering that the implicit parallelism of genetic algorithms has obvious advantages in solving sequential coding optimization problems, we design a genetic algorithm (GA) to solve the model.

4.1. Encoding

The encoding method we use is natural number encoding. We assign the transport task to the corresponding AGV, and if the code number of the \( i \)-th position is \( k \), it means that the \( i \)-th task will be executed by AGV-\( k \). In this way, a chromosome of length \( N \) can be composed of \( N \) integers arranged from 1 to \( N_{AGV} \), which is the number of AGVs participating in the scheduling task. Figure 2 shows a chromosome with a total number of 16 and gene codes of 1, 2 and 3, which means there are 16 tasks need to be completed by these 3 AGVs. And for example, the code number of the 7th position is 2, which means that task 7 will be completed by AGV2.

![Figure 2. Encoding of the chromosome.](image)

4.2. Decoding

We use a segmented decoding method to decode the chromosome, that is, transport tasks assigned to different AGVs are decoded separately, so the whole decoding process can be regarded as a combination of \( N_{AGV} \) chromosome segment decoding. Figure 3 shows the decoding process of a chromosome. Respectively, we decode the chromosome with the codes of 1, 2 and 3, and can get the time \( z_i \) when these 3 AGVs start to execute task-\( i \), which should also be greater than the minimum task start time \( A_i \). In the process, the waiting time \( tw_i \) and the no-load time \( te_{i,j} \) of each task for each AGV can also be obtained.
4.3. Genetic operator

We choose the method of random traversal sampling to select individuals, which can ensure the approximate optimal solution and the fast convergence speed of the GA. And we use single-point crossover for crossover operator, that is, only one crossover point is randomly set in the individual encoding string, and then part of the chromosomes of the two matched individuals are exchanged at this point.

The basic bit mutation operator is used for mutation, which is to randomly designate a certain locus in an individual coding string with a mutation probability, and replace the original gene value of the mutation point with other allele values.

5. Experimental Analysis

5.1. Settings of experiments

Referring to actual data of an automated container terminal, the layout of AGV road network is shown in Figure 4, where A and B represent quay cranes, a to f represent container yards, and the arrows point in the prescribed driving direction for AGVs. It takes 120s for a quay crane to unload a container. The no-load speed of an AGV is 10m/s, and the heavy-load speed is 5m/s. To evaluate the effectiveness of our scheduling model and the performance of the GA, we set up three experiments as shown in Table 1.

| Serial number | Purposes                                      | Settings                                                                 |
|---------------|-----------------------------------------------|--------------------------------------------------------------------------|
| 1             | Compare the efficiency of a mixed integer linear programming (MILP) and the GA. | Set the number of genetic algorithm individuals = 60, the maximum number of iterations = 500, the selection ratio = 0.8, and the number of variables = 5, 10, 15, 20. Repeat the experiment according to the settings. |
| 2             | Verify the impact of the optimization model on scheduling results. | Set the number of AGV configurations = 6, the total number of tasks = 100, tasks number for the container yard a to f = 20, 15, 15, 20, 20, 10. Other settings are the same as those in Experiment 1. Repeat the experiment according to the settings. |
| 3             | Verify the impact of the number of configurations AGV on scheduling results. | Set the number of AGV configurations = 5, 6, 7, 8. Other settings are the same as those in experiment 2. Repeat the experiment according to the settings. |
5.2. Experiment results

5.2.1. Experiment 1
We use the MILP and GA to solve the model respectively, and the results are shown in Table 2. We find that with the increasing number of tasks, the solution time of the MILP is much longer than that of the GA, while the accuracy of the two results is not much different. It indicates that the GA has stronger adaptability when solving a large-scale automated terminal AGV scheduling problem.

| Algorithm | Number of tasks | 5  | 8  | 10  | 15  |
|-----------|----------------|----|----|-----|-----|
| MILP      | Completion time /s | 165 | 283 | 416 | 659 |
| GA        | Completion time /s | 165 | 282 | 418 | 641 |
| MILP      | Calculation time /s | 0.11 | 3.25 | 179.43 | 458.13 |
| GA        | Calculation time /s | 10.14 | 10.23 | 10.52 | 10.29 |

5.2.2. Experiment 2
In order to verify the effectiveness of the optimization model, we select some indicators to compare the scheduling results before and after the optimization scheme. Figure 5 shows the optimized AGV scheduling schemes, and Table 3 shows the comparison of scheduling results. As shown in Table 3, the optimized scheduling mode can reduce the waiting time of quay cranes by 20.25%, which means it can greatly improve the utilization rate of quay cranes. And the waiting time and invalid operation time of AGVs are reduced by 3.47% and 6.83%, indicating that it can also improve the utilization rate of AGVs. The task completion time and total driving distance are reduced by 6.72% and 9.04%, proving that the model can effectively improve the operational efficiency of AGVs.

| AGV1 | 9  | 14  | 15  | 27  | 30  | 39  | 43  | 45  | 55  | 58  | 65  | 76  | 81  | 83  | 93  | 100 |
| AGV2 | 2  | 4   | 12  | 18  | 24  | 31  | 32  | 46  | 52  | 56  | 62  | 67  | 74  | 80  | 84  | 92  | 95  |
| AGV3 | 6  | 8   | 16  | 22  | 26  | 34  | 37  | 44  | 48  | 53  | 57  | 66  | 72  | 77  | 88  | 94  | 97  |
| AGV4 | 10 | 13  | 19  | 25  | 29  | 38  | 40  | 47  | 54  | 59  | 61  | 70  | 73  | 82  | 87  | 90  | 99  |
| AGV5 | 1  | 7   | 11  | 20  | 21  | 33  | 35  | 41  | 50  | 60  | 63  | 69  | 75  | 79  | 86  | 91  | 98  |
| AGV6 | 3  | 5   | 17  | 23  | 28  | 36  | 42  | 49  | 51  | 64  | 68  | 71  | 78  | 85  | 89  | 96  |

Figure 5. Optimized AGV scheduling schemes.

| Algorithm | Waiting time of QCs /s | 10021 | 2390 | 14871 | 6575 | 235.7 |
|-----------|------------------------|-------|-------|-------|------|-------|
| GA        | 7992                   | 2307  | 13855 | 6133  | 214.4|

5.2.3. Experiment 3
We configure different numbers of AGVs to transport tasks of the same size, and the impact on scheduling results is shown in Table 4. We compare the variations of scheduling results when increasing the number of AGV configurations from 5 to 6 and 7 to 8. The reductions of completion time are 630s and 25s, the reductions of waiting time of QC are 4,333s and 980s, which means increasing the number of AGV configurations can only improve the efficiency of AGVs and quay cranes to a certain extent, because when the number exceeds a certain value, the improvement becomes very little. Meanwhile, the increasing number of AGVs will increase their waiting time, resulting in an increase in their invalid operation time and a reduction in the average utilization rate. So, in conclusion, comprehensive consideration and evaluation are needed to determine the optimal number of AGVs.

| Before | 10021 | 2390 | 14871 | 6575 | 235.7 |
| After  | 7992  | 2307 | 13855 | 6133 | 214.4 |
| Comparison | 20.25% | 3.47% | 6.83% | 6.72% | 9.04% |
Table 4. Comparison of scheduling results of different AGV configurations.

| Number of AGVs | Waiting time of QC /s | Waiting time of AGVs /s | No-load time /s | Invalid operation time /s | Average utilization rate of AGVs | Completion time /s |
|---------------|-----------------------|-------------------------|----------------|--------------------------|---------------------------------|-------------------|
| 5             | 10325                 | 259                     | 11656          | 11915                    | 57.2%                           | 6763              |
| 6             | 5992                  | 2307                    | 11548          | 13855                    | 54.8%                           | 6133              |
| 7             | 3767                  | 4749                    | 11365          | 16014                    | 46.0%                           | 6085              |
| 8             | 2885                  | 5729                    | 11351          | 17080                    | 39.4%                           | 6060              |

5.2.4. Experiment summaries

From the above three sets of experiments, we can find out that:

- The scheduling problem is an NP-hard problem, so the MILP can only obtain an accurate solution to small-scale problems. When the problem is in a large scale, it is beyond the MILP's capability to deal with. At this time, intelligent algorithms such as genetic algorithms can do a better job.
- The second experiment reflects the impact of changes in optimization the objectives and constraints on scheduling results. The optimized scheduling mode can improve the utilization of QCs and AGVs, and also improve the operation efficiency of AGVs.
- Increasing the number of AGV configurations can reduce the task completion time to some extent and also reduce the waiting time of QCs, but at the same time it will increase the waiting time of AGVs, resulting in an increase in invalid operation time and a reduction in the average utilization rate of AGVs. So, the optimal number of AGV configurations needs to be determined by comprehensive consideration of appeal factors.

6. Conclusions

To further improve the operation efficiency of the AGV and reduce the operating costs of the automated container terminal, we considered the completion time and invalidation time of AGV operations, and construct an AGV optimal scheduling model in which various constraints are also fully considered. And we design a genetic algorithm to solve the model. Obviously, the scheduling problem of AGVs is an NP-hard problem, so the MILP can only be used to solve the problems in a small scale. For large-scale scheduling problems, intelligent algorithms such as genetic algorithms have better adaptability. By comparing the scheduling before and after optimization, we prove that the optimized scheduling model can effectively improve the utilization of QCs and AGVs, improve the operating efficiency of AGVs as well as terminals, and reduce the burden of traffic congestion, which has some certain practical significance for terminal managers and shipping companies.

Due to the complexity of scheduling problems of AGVs, many hypothetical conditions are proposed in the construction of the model in this paper, which reduces the applicability of the model in actual scenarios to some extent. So, in future research, we can consider relaxing the assumptions from some perspectives. In addition, we only qualitatively study the impact of AGV configurations number on operation efficiency. In the future, we can take the AGV configurations number as a decision variable to consider the optimal allocation quantity of AGV under different terminal equipment configuration and container arrival quantity.

Acknowledgment

This research is supported by National Key Research and Development Plan (2016YFE0201700).

References

[1] Y. Xing, K. Yin, and L. Quadrifoglio, B. Wang, “Dispatch problem of automated guided vehicles for serving tandem lift quay crane,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2273, pp. 79–86, 2012.

[2] A. Gudelj, D. Kezić, S. Vidačić, “Planning and optimization of AGV jobs by petri net and genetic algorithm,” Journal of Information & Organizational Sciences, vol. 36, pp. 99–122, February 2012.
[3] P. Angeloudis, M. G. H. Bell, “An uncertainty-aware AGV assignment algorithm for automated container terminals,” Transportation Research Part E Logistics & Transportation Review, vol. 46, pp. 0–366, March 2010.

[4] H. Fazlollahtabar, M. Saidi-Mehrabad, J. Balakrishnan, “Mathematical optimization for earliness/tardiness minimization in a multiple automated guided vehicle manufacturing system via integrated heuristic algorithms,” Robotics & Autonomous Systems, vol. 72, pp. 131-138, 2015.

[5] Y. H. Ma, Z. H. Hu, “The dispatching and scheduling problems of AGVs at automated container terminals under uncertainty conditions,” Journal of Guangxi University (Natural Science Edition), pp. 589–597, February 2016.

[6] K. G. Huo, Y. Q. Zhang, Z. H. Hu, “Research on scheduling problem of multi-load AGV at automated container terminal,” Journal of Dalian University of Technology, vol. 56, pp. 244–251, March 2016.

[7] S. M. Homayouni, S. H. Tang, O. Motlagh, “A genetic algorithm for optimization of integrated scheduling of cranes, vehicles, and storage platforms at automated container terminals,” Journal of Computational and Applied Mathematics, vol. 270, pp. 545-556, 2014.

[8] J. Luo, Y. Wu, “Modelling of dual-cycle strategy for container storage and vehicle scheduling problems at automated container terminals,” Transportation Research Part E: Logistics and Transportation Review, vol. 79, pp. 49-64, 2015.