2023 IEEE Symposium Series on Computational Intelligence (SSCI)
Mexico City, Mexico. December 5-8, 2023

A Hybrid Approach Optimizing both Terminal Resource Configuration and External Truck Waiting Time under Truck Appointment System

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***Abstract*— For the truck appointment system in a container terminal, optimizing the configuration of gate lane and yard crane based on the appointment information is the key to shorten the external truck waiting time and reduce the redundancy of terminal resource. A hybrid approach combining deep neural network and optimization model is proposed. The deep neural network is applied to predict the truck waiting time in the yard based on the yard data. The optimization configuration model for gate lane and yard crane is established by combining the predicted result. The average waiting time of trucks, the configuration of gate lanes and yard cranes before and after optimization are compared. The results show the effectiveness of the proposed approach, which also provides a new road map for optimizing container terminal resource configuration.**

Keywords—truck appointment system, configuration of container terminal resources, external truck waiting time, collaborative optimization, deep neural network

I. Introduction

With the rapid development of global container trade, the volume of container throughput increases annually. Increasing container throughput results in a greater demand for container handling at terminals, requiring terminals to handle more container operations in a shorter period of time. If a large number of external trucks arrive during certain time periods, there is congestion at the terminal gates and yards. This also has an effect on the overall operational efficacy of the terminal and the waiting time for external trucks. Conversely, during periods with low external truck arrivals, the utilization efficiency of terminal gates and yard cranes is low, resulting in idle resource waste.

Therefore, enhancing the operational efficiency of container terminals and reducing the waiting time of external trucks has become one of the optimization directions for terminal operations. In recent years, container terminals have taken many measures to reduce terminal congestion. The Truck Appointment System (TAS) has been proposed to manage truck arrivals. Specifically, the terminal divides each day into several appointment windows and restricts the number of external truck arrivals during each appointment window. Truck companies make reservations in accordance with actual conditions, and the terminal configures gate lanes and yard cranes based on the appointment information. Accordingly, through the use of the truck appointment system, gate lanes and yard cranes can be configured based on truck appointment information that matches the demands of truck operations with the supply of terminals.

The main contributions of this study are as follows. (1) This paper employs data mining techniques to analyze container yard data, specifically the relationship between the number of trucks, truck arrival distributions, yard crane configuration, and truck waiting time. (2) This paper establishes mathematical models to minimize truck waiting costs and the operational costs of gate lanes and yard cranes by optimizing the configuration of resources based on an analysis of container yard data. (3) The proposed data-driven approach requires fewer theoretical assumptions and parameter estimations during the modeling process, allowing configuration optimization by utilizing available historical data.

The rest of the paper is organized as follows. Section II provides a brief review of previous research on the configuration of gate lanes and yard cranes for the truck appointment system. Section III describes the prediction procedure of the deep neural network. In Section IV, a collaborative configuration optimization model for terminal gate lanes and yard cranes is established. In Section V, numerical experiments are conducted to confirm the efficiency of the proposed hybrid approach. The conclusion section summarizes the findings and limitations of this paper.

II. Literature Review

The problem of terminal resource configuration for the truck appointment system has been the subject of numerous scholarly investigations. This section focuses on a literature review relating to the influence of truck appointment mechanisms on the optimization of container terminal gate and yard crane configuration, as well as the estimation of truck waiting time.

Many ports experienced significant problems with congestion at terminal gates. Guan and Liu used a multi-server queuing model to strike a balance between the gate operational cost and the truck waiting cost [1]. Minh and Noi utilized the M/G/n queuing model to optimize the total cost at the gate of container terminals by managing truck arrivals and the number of service gate lanes satisfying a given service level [2]. Gracia et al. considered various booking levels for the truck appointment system to reflect the effect of daily and seasonal fluctuations in container arrivals on the efficient lane segmentation policies at the container terminal [3].

Additionally, researchers examine the interaction between the truck appointment system and yard operations. Li et al. construct a bi-objective integer model to balance the trade-off between terminals and trucks that optimizes appointment quotas and yard cranes. The result demonstrates the benefit of simultaneously balancing the workload of yard cranes [4]. Ma et al. proposed a mixed-integer bi-level programming model to simultaneously optimize the vessel-dependent time windows for inbound trucks and yard cranes. The proposed method can substantially reduce truck waiting times [5]. Li et al. created a novel three-level vocation queuing model to estimate the captains of each kind of truck movement in the terminal, as well as a bi-objective mixed integer programming model that optimizes the allocation of appointment quotas concurrently with the deployment of yard cranes [6].

The wait time for container trucks at a terminal is a key indicator of truck dispatching performance and terminal operation efficiency. Chen et al. model the queuing process of container trucks at terminals as a non-stationary M(t)/Ek/C(t) queuing system and estimate and optimize the turnaround time of container trucks at terminals using an enhanced fluid-based point-by-point steady-state approximation method [7]. In addition, Phan and Kim divided the truck turnaround time into truck transport time and truck operation time and then optimized the sub-time period to address the intra-terminal operation scheduling problem [8]. However, Chen pointed out that in the process of solving the optimal container truck turnaround time, queueing models and a large number of assumptions related to the port operation process are often involved, and it is difficult to accurately simulate the real situation; therefore, the applicability and generalization of the optimization model will not be guaranteed [9].

In the field of transportation, modern ports will utilize sensors to collect data. Using such data, some researchers have investigated methods for predicting truck waiting times. Li et al. proposed a deep learning model that combines GRU and FCNN to enhance the accuracy of daily external truck arrival predictions by incorporating vessel information, arrival working days, and weather conditions [10]. Sun et al. proposed a method that combines data mining techniques with mathematical optimization modeling methods to optimize the container truck reservation quota, analyzing the correlation between the number of external trucks entering the port and the turnaround time using polynomial fitting and robust optimization [11].

The preceding research provides a scientific foundation for the collaborative optimization of terminal gates and yard cranes. The research demonstrates that the collaborative optimization of gate lane and yard crane configurations can effectively reduce truck waiting time and enhance terminal operation efficiency. The existing related literature mainly uses queuing methods for estimating truck waiting times. Some researchers have begun to apply data-driven approaches to the prediction of truck-related information. The results demonstrate that the data-driven approach makes better use of historical data and has a greater degree of prediction accuracy. In order to enrich the study of data-driven approaches in the field of terminal resource configuration, this paper proposes a hybrid approach combining a deep neural network and an optimization model to optimize the configuration of gate lanes and yard cranes.

III. PROBLEM DESCRIPTION AND DATA PROCESSING

A. *Problem Description*

The operating subsystems involving external container trucks in terminals, including gates and yards. The external container trucks transport the containers to the terminal, and they enter the terminal through gates. The terminal gate has several lanes, and for the lanes that distinguish the operation type, the container truck driver chooses the lane according to the container truck operation type. The crossing time varies due to the various truck operation types and procedures. Typically, the crossing time for empty containers is shorter than that for loaded containers. When the arrival rate of trucks exceeds the capacity of the gate lanes, container trucks may be required to wait in line at the gate. After passing through the gate, external container trucks enter the yard, and the yard equipment completes the container pickup and delivery operations. The yard crane is the primary piece of equipment for container operations in the yard. The yard cranes need to serve both external and internal trucks. The internal trucks are responsible for horizontal transport between the yard and terminal. When the rate of truck arrival exceeds the capacity of the yard crane, the trucks also have to wait. After yard operations are completed, the external trucks eventually exit the terminal.

B. *Data Analysis and Processing*

For this study, truck and yard data from a container terminal in northeast China during a 10-day period was collected. The structure of the collected data is shown in Table 1.

TABLE I. THE KEY FIELDS OF COLLECTED DATA

Keyword	Meaning
TRUCK_ID	The ID of the truck corresponding to the container
BLOCK_ID	The ID of block
YARDCRANE_ID	The ID of yard crane
TRUCK_TYPE	The type of truck: external container truck (ET), internal container truck (IT)
WORK_TYPE	The type of container operation: empty container pickup (IE), empty container delivery (XE), loaded container pickup (IF), loaded container delivery (XF)
SEND_T	The time when the truck sends the task to the yard
COMPLETE_T	The time when the truck completes the operation

C. *Prediction of Truck Waiting Time at Yard*

In this study, data from the terminal is collected by the hour for ten days (a total of 240 hours). By aggregating the data based on blocks, the number of containers in block *b* in time period p can be obtained, including the number of empty container pickup by external trucks $N_{p,b}^{ET,IE}$, empty container delivery by external trucks $N_{p,b}^{ET,XE}$, loaded container pickup by external trucks $N_{p,b}^{ET,IF}$, loaded container delivery by external trucks $N_{p,b}^{ET,XF}$, empty container pickup by internal trucks $N_{p,b}^{IT,IE}$, loaded container delivery by internal trucks $N_{p,b}^{IT,XF}$, loaded container pickup by internal trucks $N_{p,b}^{IT,IF}$, and empty container delivery by internal trucks $N_{p,b}^{IT,XE}$. $h_{p,b}$ is the number of yard cranes serving the block b in each time period p and $r_{p,b}$ is whether the block b in time period p involves vessel loading and unloading operations.

The truck waiting time in the yard is calculated using SEND_T and COMPLETE_T.

$$t_p^i = Com_p^i - Send_p^i \tag{1}$$

$$T_p^b = \sum_i t_p^i i_p^b \tag{2}$$

where Com_p^i and $Send_p^i$ represent the completion time of the truck i in the yard and the time when the truck i sends task to the yard for time period p, respectively. t_p^i represents the waiting time of the truck i in the yard for the time period p. i_p^b is a binary variable indicating whether the truck i in the time period p belongs to block b. T_p^b represents the waiting time of internal and external trucks in the block b for the time period p.

Most studies presume a Poisson distribution for the number of trucks arriving at the yard. Skewness and kurtosis are introduced in order to analyze the impact of the degree of concentration in yard operations on truck waiting times for the same number of trucks. Skewness quantifies the degree and direction of asymmetry in a statistical distribution, whereas kurtosis quantifies the peak height of the probability density distribution curve. The skewness and kurtosis of truck operation task arrivals in each block during each time period are calculated using (3) and (4).

$$\text{Skew}_{p,b} = E\left[\left(\left(N_{p,b} - \mu_{p,b}\right)/\sigma_{p,b}\right)^3\right] \tag{3}$$

$$\text{Kurt}_{p,b} = E\left[\left(\left(N_{p,b} - \mu_{p,b}\right)/\sigma_{p,b}\right)^4\right] \tag{4}$$

The construction of a prediction model based on a deep neural network with truck data and yard data as input. The output is the predicted truck waiting time in the yard. The middle layer is the hidden layer. The deep neural network is capable of fitting the nonlinear relationship between terminal data and truck waiting time in the yard.

The input layer input is X_i, W_i and b_i are the weight matrix and bias vector of layer i in the deep neural network, respectively, a_i denotes the output vector of layer i. The hidden layer uses Rectified Linear Units (ReLU) as the activation function, and the output layer output the truck waiting time in the yard. The mean square error function is selected as the loss function of the deep neural network. ReLU is fast in computation, and the non-saturation of ReLU can effectively solve the problem of gradient disappearance and slow down the generation of over-fitting.

$$\begin{aligned} a_i &= \phi_{hi}\left(W_i X + b_i\right) \\ \phi_{hi} &= \mathrm{Re}LU(x) = \begin{cases} x, & \text{if } x > 0, \\ 0, & \text{if } x \le 0. \end{cases} \end{aligned} \tag{5}$$

Root mean square error (RMSE) and mean percentage absolute error (MAPE), are used to measure the prediction effect of the deep neural network, which is calculated as (6) and (7), where $\hat{y}$ is the predicted value of the waiting time of the test set of trucks in the yard and y is the actual value.

$$\text{RMSE} = \left(\frac{1}{n}\sum_{k=1}^{n}\left(\hat{y}_k - y\right)^2\right)^{1/2} \tag{6}$$

$$\text{MAPE} = \frac{1}{n}\left(\sum_{k=1}^{n}\left|\hat{y}_k - y_k\right| / y_k\right) \tag{7}$$

IV. Optimization Modeling and Solution

A. Model Description

The truck waiting time is an essential indicator of the efficiency of terminal operations. The configuration of the gate lanes and yard cranes has the most effect on truck waiting times. Therefore, it is important to optimize the configuration of gate lanes and yard cranes in accordance with the principles of demand orientation and supply-demand balance.

To solve the above problem, traditional studies establish queuing models to investigate the effect of gate lane and yard crane service efficacy on the queuing of container trucks. At the gate, the queuing can be regarded as multiple parallel M/M/1 queuing and at the yard as M/Ek/c queuing. In this paper, it is assumed that the trucks arrive at the gate according to a Poisson distribution and that the gate service time follows an exponential distribution after data analysis. Using the previously described deep neural network, the duration between the truck entering the yard and the completion of yard operations is obtained.

The first stage is to optimize the configuration of the gate lane, and the gate lane has been divided into four types of dedicated lanes: delivery of empty containers, pickup of empty containers, delivery of loaded containers, and pickup of loaded containers. The dedicated lane can transfer service types between each period. The terminal configures dedicated lanes for various truck operation types based on the reservation information from the truck reservation system. The second stage is to optimize the configuration of the yard cranes in each block based on the number of trucks that passed through the gate in the first stage.

In this paper, the following conditions are assumed: each container truck is tasked with transporting one TEU per journey, without taking into account a single truck transporting multiple containers; during each appointment period, the configuration of the gate lanes and yard cranes will not change; the reserved trucks will arrive according to the appointment period, regardless of missed appointments.

B. Parameters and Variables

- Parameters

p : The appointment period, $p = 1, 2, \cdots, P$

i : The time interval, each appointment period p will contain τ time intervals, the decision period is divided into small time intervals $(t_{i-1}, t_i], i = 1, 2, \cdots, T, T = \tau P$, and one of the moments in the interval is substituted for that interval

w : The operation type of the container truck task, $w = 1, 2, 3, 4$; for picking up empty container, delivering empty container, picking up loaded containers, and delivering loaded containers

r : The serial number of gate lane, $r = 1, 2, \cdots, R$

b : The serial number of block, $b = 1, 2, \cdots, B$

H : The number of available yard cranes

N_{bwp} : The number of external container trucks booked in appointment period p in the block b for the operation type w

c_1 : The waiting cost per hour per truck at the terminal

c_2 : The operating cost per hour each gate lane

c_3 : The operating cost per hour each yard crane

μ_{rwi}^g : The service efficiency when the gate lane r in the time interval i is operation for type w

M_{bwp} : The number of internal container trucks arriving at the block b for operation with type w in appointment period p

- Intermediate variables

λ_{bwi}^g : The number of external truck arrivals in the block b with the operation type w in the time interval i

λ_{rwi}^g : The number of external truck arrivals at the gate lane r with the operation type w in the time interval i

l_{rwi}^g : The queue length for the external truck at the gate lane r with operation type w in the time interval i ;

d_{rwi}^g : The number of external truck completed operation when the gate lane r with the operation type w in the time interval i

ρ_{rwi}^g : The utilization efficiency of the gate lane r with the operation type w in the time interval i

q_p^g : The average waiting time for external trucks at the gate in the appointment period p

λ_{wi}^y : The number of external trucks arrivals with the operation type w in the time interval i

λ_{bwi}^y : The number of external trucks arrivals with the operation type w in the block b in the time interval i

ε_{bp} : The kurtosis of the arrival of container trucks in the block b in the appointment period p

φ_{bp} : The skewness of the arrival of container trucks in the block b in the appointment period p

r_{bp} : Whether the block b in the appointment period p is in the ship loading and unloading period

q_p^y : The average waiting time for trucks in the yard in the appointment period p

s_{wp} : The total number of gate lanes with the operation type w in the appointment period p

- Decision variables

x_{rwp} : Boolean variables, the value is 1 if the gate lane r serving container trucks with operation type w in the appointment period p , otherwise it is 0

h_{bp} : Integer variable, the number of yard cranes configured in the block b in the appointment period p

C. Mathematical Model

The configuration under the truck appointment system involves the common interests of the terminal operator and the truck company. The objective function is shown in (8), which consists of three costs, the first one is the waiting cost of external trucks at the gate and the waiting cost of internal and external trucks in the yard; the second one is the gate operation cost, which is related to the number of gates operated in each appointment period; the third one is the yard crane operation cost, which is related to the number of yard cranes operated in each block in each appointment period.

$$\min F = c_1\left(\sum_{p=1}^{P}\sum_{r=1}^{R} f_{rp}^g + \sum_{p=1}^{P}\sum_{b=1}^{B} f_{bp}^y\right) + c_2\left(\sum_{p=1}^{P}\sum_{w=1}^{W}\sum_{r=1}^{R} x_{rwp}\right) + c_3\left(\sum_{p}^{P}\sum_{b}^{B} h_{bp}\right) \tag{8}$$

$$\sum_{w}^{W} x_{rwp} \le 1 \tag{9}$$

$$\sum_{r}^{R} x_{rwp} \ge 1 \tag{10}$$

$$\sum_{r}^{R}\sum_{w}^{W} x_{rwp} \le G \tag{11}$$

$$s_{wp} = \sum_{r}^{R} x_{rwp} \tag{12}$$

$$\lambda_{bwi}^g = N_{bwp} / \tau \tag{13}$$

$$\lambda_{rwi}^g = \sum_{b}^{B} \lambda_{bwi}^g \Big/ s_{wp} \tag{14}$$

$$l_{rwi}^g = \rho_{rwi}^g / \left(1 - \rho_{rwi}^g\right) \tag{15}$$

$$l_{rw(i+1)}^g = \max\left\{l_{rwi}^g + \lambda_{rwi}^g - d_{rwi}^g, 0\right\} \tag{16}$$

$$d_{rwi}^g = \mu_{rwi}^g \cdot \rho_{rwi}^g \tag{17}$$

$$q_{rp}^{g} = \sum_{i=\tau(p-1)+1}^{\tau p} \sum_{w=1}^{W} l_{rwi}^{g} x_{rwp} \Big/ \sum_{i=\tau(p-1)+1}^{\tau p} \sum_{w}^{W} d_{rwi}^{g} x_{rwp} \quad (18)$$

$$\lambda_{i}^{y} = \sum_{r}^{R} \sum_{w}^{W} d_{rwi}^{g} \quad (19)$$

$$\lambda_{bwi}^{y} = \lambda_{bwi}^{g} \lambda_{i}^{y} \Big/ \sum_{r}^{R} \lambda_{rwi}^{g} x_{rwi} \quad (20)$$

$$\sum_{b}^{B} h_{bp} \le H \quad (21)$$

$$0 \le h_{bp} \le 2 \quad (22)$$

$$q_{bp}^{y} = f\left(\sum_{i=\tau(p-1)+1}^{\tau p} \lambda_{bwi}^{y}, M_{bwp}, \varepsilon_{bp}, \varphi_{bp}, h_{bp}, r_{bp} \right) \quad (23)$$

Equation (9) indicates that each gate lane can serve at most one type of container truck operation in each appointment period. Equation (10) indicates that at least one gate lane is assigned to each operation type in each appointment period. Equation (11) shows that the sum of the lanes configured during any appointment period is less than the total number of gate lanes. Equation (12) calculates the total number of gate lanes for each operation type during the appointment period. Equation (13) represents the container truck arrivals in each appointment period converted into the time interval. Equation (14) denotes the arrival of external container trucks at the gate lane r during time interval i. External trucks with operation type w arriving at the gate during time interval i evenly enter the operated dedicated gate lane to receive service. Equation (15) represents the number of external container trucks queuing at the gate, which is derived from the queuing model formula. Equation (16) represents the relationship between the queue length of container trucks at the next time interval and this time interval. Equation (17) denotes the number of external container trucks enter terminal during time interval i. Equation (18) denotes the average waiting time for external container trucks at the gate. Equation (19) denotes the total number of external container trucks entering the yard in time interval i is equal to the total number of external container trucks leaving the gate in time interval i. Equation (20) calculates the number of external container trucks arriving at the block b. Equation (21) indicates that the sum of the yard cranes configured in the block in each appointment period is less than the total number of yard cranes. Equation (22) indicates that the number of yard cranes configured in the same block in any each appointment period is no more than two. Equation (23) indicates the average waiting time of container trucks in the yard.

The gate lane and yard crane configuration optimization model is a nonlinear integer programming problem, and it is challenging for the existing constraint solver to find the optimal solution in a satisfactory amount of time. Therefore, this paper proposes a genetic algorithm for solving the model. First, the initial population is created using real-number coding. According to the objective function, the fitness value of the individuals corresponding to each chromosome is calculated. For chromosome selection, the roulette wheel strategy is used. This paper applies the single-point period crossover method to generate a new child in order to satisfy the model constraints. The operation is terminated when the evolutionary generation of the algorithm reaches the maximum number of iterations.

V. NUMERICAL ANALYSIS

This paper analyzes real data from a container terminal in northeast China as a case study. In the case study, there are 6 lanes at the gate, 12 blocks in the yard, and 16 yard cranes serving internal and external container trucks. With a decision period of 12 hours, the decision period is divided into 12 appointment periods, so the length of each appointment period is one hour. Each lane at the gate obeys the M/M/1 queueing model, and the throughput of the truck lane is limited to [50, 50, 45, 40] per hour for picking up empty containers, delivering empty containers, picking up loaded containers, and delivering loaded containers. The waiting cost of each container truck at the terminal is 40 per hour, the operating cost of each gate lane is 20 per hour, and the operating cost of the yard crane is 150 per hour.

A. Results Analysis of the Truck waiting Time in the Yard

The number of input layer neurons is 12, which represents the number of internal and external container trucks with four operation types, the kurtosis and skewness of the container operation, the number of yard cranes in the block, and whether the block is in a ship loading and unloading period. The number of output layer neurons is 1, which represents the truck waiting time in the yard. The total data is split using the train_test_split function, where 90% is the training data set and 10% is the test data set. The learning rate is set to 0.1, and the discard value is 0.5.

The results of the prediction are shown in Fig. 2. On the test data, the prediction results of two different prediction methods, namely Deep Neural Networks and Elastic Net Regression, are included. The results demonstrate that the Deep Neural Network provides more precise predictions than Elastic Net Regression. Both the RMSE and MAPE of the Deep Neural Network are reduced by more than 20% compared to the Elastic Net Regression in the test data set, indicating that the model has great generalization. In addition, it proves the effectiveness of Deep Neural Networks in predicting truck waiting times.

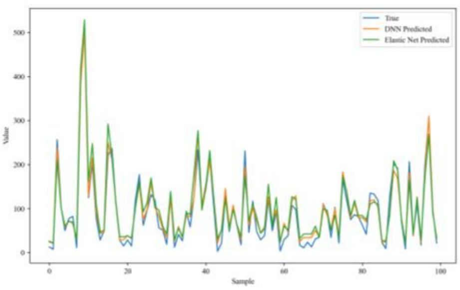

Fig. 1. The prediction results of Deep Neural Network and Elastic Net Regression

TABLE II. THE COMPARISON OF THE PREDICTION RESULTS

Deep Neural Network		**Elastic Net Regression**	
RMSE	***MAPE***	***RMSE***	***MAPE***
16.63	0.039	23.58	0.057

A comparison of the results of the Deep Neural Network and queuing theory is shown in Table 3. The test set consisted of twelve consecutive hours of data on a given day, and the method proposed by Guan was used to calculate the truck waiting time in the yard [1]. Compared with queueing Theory, the prediction accuracy of the Deep Neural Network is greater. The RMSE and MAPE of the Deep Neural Network model are reduced by more than 50%. The Deep Neural Network is able to better mine the operational characteristics from historical data and can more accurately predict the truck waiting time in the yard by combining information such as vessel loading and unloading schedules.

TABLE III. THE COMPARISON OF DEEP NEURAL NETWORK AND QUEUING THEORY

Deep Neural Network		**Queuing Theory**	
RMSE	***MAPE***	***RMSE***	***MAPE***
18.37	0.044	55.94	0.102

B. *Results Analysis of the Optimization Model*

The results before and after optimization are shown in Table 4. Before configuration optimization, all the gate lanes were in use, with a total of 72 units gate lanes operated, and the average waiting time for the external container truck at the gate was 3.75 minutes. After configuration optimization, the average waiting time for external container trucks is 3.82 minutes, an increase of 0.07 minutes, with a total of 64 units gate lanes operated and a decrease in operating costs of 8 unit lanes. Thus, it is evident that adjusting gate lane operations based on appointment information can reduce gate lane resource redundancy without significantly increasing truck waiting times. Before configuration optimization, the average waiting time for trucks in the yard was 17.93 minutes; after configuration optimization, it decreased to 15.77 minutes, a 2.18-minute decrease. The number of deployed yard cranes remained unchanged at 152. By optimizing the quantity of yard cranes based on appointment information, it is possible to reduce truck waiting time in the yard without increasing equipment.

Before configuration optimization, the cost of trucks at gates and yards was 17,488, while the operating cost at the gate was 1,440 and the operating cost at the yard was 22,800. After configuration optimization, the cost of trucks is 15,802, the operating cost at the gate is 1,280, and the operating cost at yards is 22,800. The total cost was reduced from 41,728 to 39,882. The results indicate that the hybrid approach can be used to more effectively configure available resources, reduce truck waiting time at the terminal.

TABLE IV. THE COMPARISON OF THE OPTIMIZATION MODEL RESULTS

Configuration model	**Waiting time**			**Number of configured**	
	At gate	***At yard***	***Total***	**Gate lanes**	**Yard cranes**
Before optimization	3.75	17.93	21.68	72	152
After optimization	3.82	15.77	19.59	64	152

VI. CONCLUSION

In this paper, a hybrid approach is proposed that optimizes both container terminal resource configuration and external truck waiting time under the truck appointment system. The hybrid approach combines an optimization model of gate lane and yard crane configuration with the Deep Neural Network for predicting the truck waiting time in the yard.

The prediction results of the Deep Neural Network and the Elastic Net Regression are compared. It is demonstrated that the prediction results of the Deep Neural Network are more accurate. The prediction results of the Deep Neural Network and the queuing theory proved that the Deep Neural Network can use historical data more effectively to predict the truck waiting time in the yard. By analyzing the result before and after optimization, it is shown that the hybrid approach can effectively configure terminal resources, reduce the truck waiting time, and decrease the redundancy of resource allocation.

For future research, our work will consider the transfer operation of gate lanes and the movement of yard cranes between blocks. And we will further analyze the dedicated gate lanes and general gate lanes.

ACKNOWLEDGMENT

This research is partially supported by National Natural Science Foundation of China (72172023, 72171032, 72202025).

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