DATA AND MODEL DUAL-DRIVEN APPROACH OPTIMIZING APPOINTMENT QUOTA OF EXTERNAL CONTAINER TRUCK

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1. **ABSTRACT:** The truck appointment system sets quotas for each period to control the volume of external trucks arriving at the port. Optimizing appointment quotas is crucial for reducing the dwell time of external trucks and enhancing the utilization of terminal resources. Therefore, a method that combines data-driven and model-driven approaches was proposed to optimize appointment quotas by leveraging historical data. Gaussian process regression was employed to mine the correlation between the number of external trucks arriving at terminals and the truck turnaround time under different operation types in each appointment period. The objective was to minimize waiting costs for external trucks and transfer costs associated with deviations from the expected arrival periods. A non-linear mixed-integer programming model was formulated, and a genetic algorithm was designed for its solution to optimize appointment quotas under different operation types in each appointment period. The data-driven results indicate that Gaussian process regression yields a 2% lower relationship error than polynomial regression. The optimization model, which refined the operation types, reduces the total cost by 5.13% compared to traditional methods and decreases the extreme variance of appointment quotas by 64%.

2. INTRODUCTION

The operational tasks within China's main ports expand significantly as the throughput of the ports develops. The large amount of external container trucks arriving at the port has disrupted the balance of container terminal operations, leading to a decrease in gate and yard efficiency. This has also caused longer waiting times for external container trucks [1]. Hence, enhancing the effectiveness of in-port operations and minimizing the waiting time for external trucks has become a prominent concern for terminal operators.

Based on the congestion problem caused by the mass arrival of container trucks, Giuliano *et al.* suggested implementing the truck appointment system. This system involves the port determining the length and the maximum arrival number in each appointment period. The determinations are based on the operational configurations of the yard and gate. The system requires that external trucks that have successfully made a reservation must arrive at the gate during the chosen appointment period [2]. The research demonstrates that implementing the truck appointment system can significantly decrease the waiting time of external trucks, improve the efficiency of terminal operations, and minimize the total operational costs [3-4].

In the field of truck appointment systems, some scholars focus on the smooth arrival of trucks by optimizing the truck appointment quota. Existing literature on optimizing the appointment quota can be divided into two main categories: model-driven approaches and data-driven approaches. Several scholars rely on model-driven approaches to create a conventional operations model for optimizing the truck appointment quota. Zhang *et al.* developed a BCMP queuing network to represent the queuing process of trucks at terminals. They devised a solution using a genetic algorithm and pointwise stationary fluid flow approximation (PSFFA) [5]. According to Julio *et al.*, the goal of managing container terminals is to optimize the truck appointment quotas in order to achieve a balance between supply and demand [6]. Ramírez-Nafarrate *et al.* constructed a discrete event simulation model and heuristic procedure to assess the effects of the truck appointment system on container reloading [7]. He *et al.* devised a model to jointly optimize the appointment of external trucks and schedule automatic rail-mounted gantry cranes (ARMG) in the yard [8]. Li *et al.* proposed a hierarchical queuing network with prioritization to estimate the length of the truck queue and optimize the truck appointments for each block [9].

Recently, some researchers summarized the principles of operation by analyzing historical data using data-driven approaches and enhanced terminal operations by integrating the data analysis findings. Several scholars have used data-driven approaches to predict truck traffic flow and activity [10-12]. Azab *et al.* suggested using a simulation-based optimization method to arrange the scheduling of truck appointments [13]. Caballini *et al.* optimized the truck appointment quotas by clustering the demand for truck operation tasks and constructing a model [14]. Kim and Ye employ information connected with truck arrivals to minimize the rehandling operations of containers [15]. Li *et al*. have created a sophisticated deep learning model that combines the Gated Recurrent Unit (GRU) and Fully Connected Neural Network (FCNN) to accurately forecast daily container arrivals by taking into account vessel information, arrival weekdays, and weather conditions [16]. Sun *et al.* presented a method that combines data mining and robust optimization to enhance the appointment quota [17].

Some scholars have also endeavored to utilize other machine-learning approaches in transportation. Some scholars have identified the potential of Gaussian process regression and employed Gaussian process regression to forecast the truck travel time and the vessel turnaround time [18-19]. Liu *et al.* determined that Gaussian process regression exhibits significant promise in estimating and predicting transportation systems, including traffic flow analysis [20].

The previous study demonstrates that optimizing the truck appointment quota makes it possible to achieve the smooth arrival of trucks and alleviate the congestion in the terminal. Recently, researchers have utilized data-driven approaches to investigate the relationship between the number of external trucks and the truck turnaround time. Data-driven approaches have the advantage of using historical data compared to model-driven approaches. Several scholars have demonstrated the significant potential of Gaussian process regression in analyzing transportation systems. Gaussian process regression has the advantages of reducing data requirements, decreasing computational complexity, and improving the model interpretability. Prior research has examined using the Gaussian regression process in urban traffic systems. However, further investigation is required to explore the application of the Gaussian regression process in analyzing container truck traffic flow.

The paper proposes an external container truck appointment quota optimization model that combines both data-driven and model-driven. The approach includes the Gaussian regression process and programming model, and it is based on historical data collected from a terminal in northeastern China. The data-driven approach analyzes the relationship between the number of arriving external trucks and the truck turnaround time for different operation types during each appointment period. The programming model is formulated using the relationship obtained by the data-driven approach. The model aims to minimize the waiting costs of external trucks and the transfer costs based on the deviation between the allocated period and the preferred period for each truck. The dual-driven approach optimizes the truck appointment quota, ensuring the smooth arrival of trucks.

The key contributions of this paper are as follows. The non-parametric characterization of the number of trucks and the truck turnover time were described by Gaussian process regression. The result was compared with the regression model of parameter characterization. The truck appointment quota optimization model considers the impact of the operation type of container truck. Additionally, the cost parameter is used to prioritize heavy container operations.

3. DUAL-DRIVEN APPROACH TO OPTIMIZE TRUCK APPOINTMENT QUOTA

3.1 General framework

The research framework of this paper is illustrated in Figure 1. It presents an approach for optimizing the truck appointment quota at container terminals. The approach combines the Gaussian regression process with a programming model. Firstly, the unprocessed terminal data is clustered according to the truck operation type and the arrival period. Then, the Gaussian process regression was used to establish the relationship between the number of external container truck arrivals and the truck turnaround time in each period. A programming model was developed to optimize appointment quotas for various truck operation types. The model considers the time it takes to complete a container truck task and the deviation between the truck allocated and preferred periods.

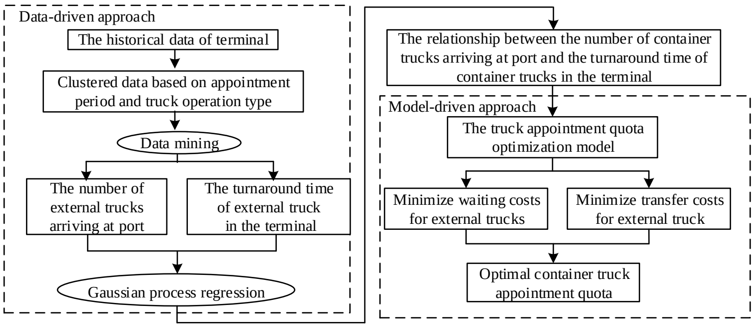

Figure 1: The framework for optimizing the truck appointment quota using the dual-driven approach

3.2 Data-driven approach

The container trucks were categorized based on their purpose. The study investigated the relationship between the number of external trucks arriving and the truck turnaround time for each operation type in each appointment period.

3.2.1 Data Collecting Principles

The key fields of the collected data are shown in Table 1.

Table 1. The key fields for data collection

Key fields	*meaning*
CNTR_ID	The ID of the container
TRUCK_ID	The ID of the truck associated with the container
GATE_IN_DT	The timestamp of the container truck arrived at the terminal
GATE_OUT_DT	The timestamp of the container truck departing from the terminal
OPERATION_TYPE	The operation type of truck: picking up empty containers, delivering heavy containers, picking up heavy containers, delivering empty containers

The unprocessed data are clustered based on the appointment period and truck operation type. The number of container trucks arriving and the truck turnaround time for each operation type in each appointment period are obtained. The truck turnaround time is determined by analyzing the terminal gate system data, including the recorded arrival and departure timestamps of external container trucks.

$$t_{ip} = Out_{ip} - In_{ip} \tag{1}$$

$$T_{wp} = \sum_i t_{ip} i_{wp} \tag{2}$$

$$M_{wp} = \sum_i i_{wp} \tag{3}$$

In_{ip} and Out_{ip} are the arrival and departure timestamps for the external container i in the appointment period p, respectively; t_{ip} is the truck turnaround time for the external container i in the appointment period p; i_{wp} is a parameter of 0,1, indicating whether or not the external container i in the appointment period p is for truck operation type w; T_{wp} is the total truck turnaround time in the appointment period p for truck operation type w; M_{wp} is the number of external containers for truck operation type w that have the arrival at the port in the appointment period p.

3.2.2 Gaussian process regression

Based on the historical data of the terminal, Gaussian Process Regression was used to investigate the number of external container trucks arriving and the truck turnaround time for each operation type in each appointment period. Gaussian process regression is a nonparametric statistical model that models data similarity. It assumes the data follows a Gaussian process with mean and covariance functions.

To verify the fitting effect of Gaussian process regression between M_{wp} and T_{wp}, the dataset for each operation type is divided into two parts: the training dataset is used to train the model, while the test dataset is used to evaluate the accuracy. It is done by using the train_test_split function from the sklearn package to split the data, with 80% for the training dataset and 20% for the testing dataset.

It is assumed that the regression function between M_{wp} and T_{wp} is $T_{wp} = f(M_{wp}) + \varepsilon$, and $\varepsilon \sim N\left(0, \sigma_n^2\right)$ is noise coefficient. $X = \left(x_1, \cdots, x_n\right)^{\mathrm{T}}$ and $Y = \left(y_1, \cdots, y_n\right)^{\mathrm{T}}$ are M_{wp} and T_{wp} in the training dataset and x^* is M_{wp} in the test dataset. It is given that the mean is 0 and the covariance is the Gaussian kernel function $k(x, x^*) = \sigma_f^2 \exp\left[-(x - x^*)^2 / 2l^2\right]$, estimation σ_f and l under the maximum value of $\log(y|X) = -1/2(\log|K_{XX}| + n\log 2\pi + y^T(K_{XX} + \sigma_n^2 I_n)^{-1} y)$. According to the Eqs. (4-5) to find the mean $h\left(x^*\right)$ and the variance estimation $\operatorname{cov}\left(x^*\right)$ of T_{wp} corresponding to each M_{wp} in the test dataset. The accuracy of the Gaussian process regression will be measured by the coefficient of determination R^2 and the mean absolute percentage error(MAPE) of the test results.

$$h\left(x^*\right)=K_{x^*X}\left(K_{XX}+\sigma_n^2 I_n\right)^{-1}Y \tag{4}$$

$$\operatorname{cov}\left(x^*\right)=K_{x^*x^*}-K_{x^*X}\left(K_{XX}+\sigma_n^2 I_n\right)^{-1}K_{Xx^*} \tag{5}$$

$K_{XX}=K(X,X)=\left(k\left(x_i,x_j\right)\right)_{n\times n}$ is the covariance matrix; $K_{Xx^*}=K\left(X,x^*\right), K_{x^*X}=K_{Xx^*}{}^T$ is the covariance matrix between the test point x^* and the training dataset X ; $K_{x^*x^*}=K\left(x^*,x^*\right)$ is the covariance of the test point x^* ; I_n is the unit matrix; σ_n^2 is the noise variance.

The Gaussian process regression can be used to obtain the mean and variance of T_{wp} corresponding to M_{wp} . The mean of T_{wp} is evaluated as the main prediction result and introduced into the subsequent programming model. Eq. (6) expresses the relationship between T_{wp} and M_{wp} in the programming model.

$$T_{wp}=f(M_{wp}) \tag{6}$$

3.3 Model-driven approach

The mean and variance of the total truck turnaround time T_{wp}, obtained from the number of external trucks M_{wp} by the data-driven approach, are used to establish a programming model for optimizing the truck appointment quota in each period. It is assumed that the length of each period is one hour. The arriving trucks must make appointments and arrive at the port during the chosen appointment period.

3.3.1 Parameter setting

W : The set of truck operation types, including picking up empty containers, delivering heavy containers, picking up heavy containers, and delivering empty containers, $W=\{1,2,3,4\}, w\in W$.

P : The set of appointment periods. The length of each period is equal. $P=\{1,\cdots,p,\cdots,|P|\}, p\in P$.

N_{wp} : The number of external container trucks for operation type w preferred arrival terminal in the appointment period p before optimization.

δ_w : The maximum deviation range between the allocated period and the preferred period for the truck for operation type w .

α_w : The unit transfer cost for the external container truck for the operation type w .

c_w : The unit waiting cost for the external container truck for the operation type w .

m_w : The maximum number of allowed arrival trucks for each appointment period for operation type w .

3.3.2 Intermediate variables

T'_{wp} : The total turnaround time of trucks arriving at the terminal during the appointment period p for operation type w , based on the results of the data driven approach.

3.3.3 Decision variables

n_{wp} : The optimized truck appointment quota for operation type w during the appointment period p.

g_{wpq} : The number of external trucks for operation type w transferred from the appointment period p to the appointment period q after optimization

3.3.4 Programming modeling

$$\min Z = \sum_{w=1}^{W}\left[\sum_{p=1}^{P} c_w T'_{wp} + \sum_{p=1}^{P}\sum_{q=p}^{P} \alpha_w \left| g_{wpq}\left(q-p\right)\right|\right] \tag{7}$$

$$n_{wp} = N_{wp} + \sum_{q=1}^{|P|} g_{wqp} - \sum_{q=1}^{|P|} g_{wpq}, \forall w \in W, p \in P \tag{8}$$

$$\sum_{p=1}^{|P|} n_{wp} - \sum_{p=1}^{|P|} N_{wp} = 0, \forall w \in W \tag{9}$$

$$T'_{wp} = f(n_{wp}), \forall w \in W, p \in P \tag{10}$$

$$g_{wpq} = 0, \forall q \notin \left(\max\left(0, p-\delta_w\right), \min\left(|P|, p+\delta_w\right)\right) \tag{11}$$

$$n_{wp} \le m_w, \forall w \in W, p \in P \tag{12}$$

$$g_{wpq}, n_{wp} \in \mathbf{N} \tag{13}$$

$$T'_{wp} \in \mathbf{R} \tag{14}$$

Eq. (7) is the objective function, which aims to minimize the cost associated with waiting time for external trucks and the transfer cost associated with the deviation between the allocated period and the preferred period for external trucks. The constraints are as follows. Eq. (8) states that the appointment quota for each truck operation type in each period p is equal to the sum of the number of trucks preferred to arrive before optimization and the number of containers transferred after optimization; Eq. (9) constrains that the total appointment quota after optimization must satisfy the container arrivals within the decision period; Eq. (10) defines the total truck turnaround time after optimization, which is calculated using the relationship obtained from Gaussian process regression; Eq. (11) limits the deviation between the allocated period and the preferred period for the truck to fall within the acceptable range, and there are no container trucks allowed to exceed this range. Eq. (12) indicates that after optimization for each operation type in each period, the truck appointment quota does not exceed the maximum number of allowed arrival trucks. The resource configuration of the terminal determines the maximum number; Eqs. (13-14) indicate the range of decision variables and intermediate variables.

3.4 The solution of the dual-driven method

Due to nonparametric inscribed restrictions in the programming model, solving it using commercial solvers becomes challenging without parameterization. However, parameterizing the data-driven results will compromise the accuracy. Hence, the genetic algorithm is employed for problem-solving.

3.4.1 Encoded form

Each chromosome consists of four genes, each representing one of the four truck operation types. Each gene contains all the appointment periods in the decision period, and each appointment period contains $\left[2\max(\delta_w)+1\right]$ genes. Figure 2 shows a schematic of the chromosomes, where $\delta_w = 2$, from top to bottom, it indicates the truck pickup of empty containers, truck delivery of heavy containers, truck pickup of heavy containers, and truck delivery of empty containers. Each period consists of five genes. As exemplified by $w=1, p=2$, the first gene represents the number of trucks transferred from the appointment period $p=2$ to $p=0$, and the value of this gene is 0 because $p=0$ exceeds the range for the decision period; the second gene value is 5, indicating that the number of trucks transferred from the appointment period $p=2$ to $p=1$ is 5; since the acceptable range is limited by, there will not be any case that the trucks booked in the $p=2$ are transferred to the $p=5...|P|$.

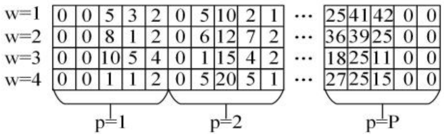

Figure 2: The schematic of the coding of a chromosome

3.4.2 Fitness function

The fitness is calculated by the objective function, which includes the waiting cost and the transfer cost. To enhance the selection ability, the objective function of the model is dynamically linearly transformed. The fitness value y' of each chromosome is calculated using Eq. (15), where $\xi^0 = M$, $\xi^k = \xi^{k-1} r$, $r \in [0.9, 0.999]$. The average fitness of the population and the sorting of individual fitness is obtained based on f' . y is the fitness before the dynamic linear transformation.

$$y' = y_{\max} - y + \xi^k \tag{15}$$

3.4.3 Selection, crossover and mutation

Roulette is employed for selection, and uniform crossover is used for crossover. The crossover is carried out for each appointment period for each gene of the parent, as shown in Figure 3. The crossover probability is obtained by Eq. (16) to avoid the algorithm from falling into a locally optimal solution.

$$pc = \begin{cases} pc_1 / (pc_1 - pc_2) + e^{(N_1 - N_2)/(N_3 - N_2)}, N_1 \geqslant N_2 \\ pc_1, N_1 < N_2 \end{cases} \tag{16}$$

N_1 is the order of the larger fitness value of the two selected chromosomes; N_2 is the order of the average fitness value of the population; N_3 is the order of the maximum fitness value of the population; pc_1 and pc_2 are the maximum and minimum value of the crossover probability, respectively.

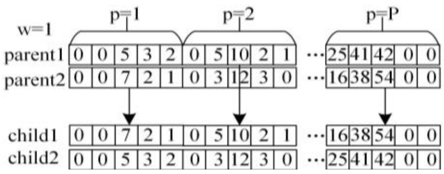

Figure 3: The schematic of the crossover of a chromosome

The mutation involves randomly disrupting the sequence inside each appointment period of each gene in the parent generation, as shown in Figure 4. The mutation probability pm is adjusted according to the number of generations by Eq. (17), pm_1 and pm_2 are the maximum and minimum values of the mutation probability, $iter$ and $iter_{\max}$ are the current number and the maximum number of iterations.

$$pm = pm_1 - \left(pm_1 - pm_2\right) iter / iter_{\max} \tag{17}$$

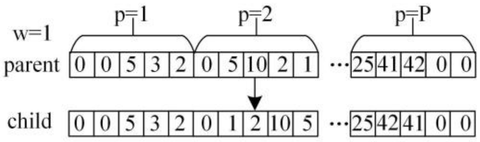

Figure 4: The schematic of the mutation of a chromosome

4. NUMERICAL ANALYSIS

4.1 The analysis of the data-driven approach

In this paper, the data from a container terminal in China in April 2021 is collected. Gaussian process regression is applied to analyze the relationship between the number of external trucks arriving and the total truck turnaround time in each appointment period for each truck operation type. The results of the Gaussian process regression are shown in Table 2. The relationship between the number of external trucks and the total truck turnaround time is shown in Figure 5. The Gaussian process regression predicts the test dataset with high accuracy. The MAPEs are all below 10% and R^2 are greater than 0.95, confirming the effectiveness of Gaussian process regression in analyzing the relationship between the number of arrival external trucks and the total truck turnaround time for four truck operation types.

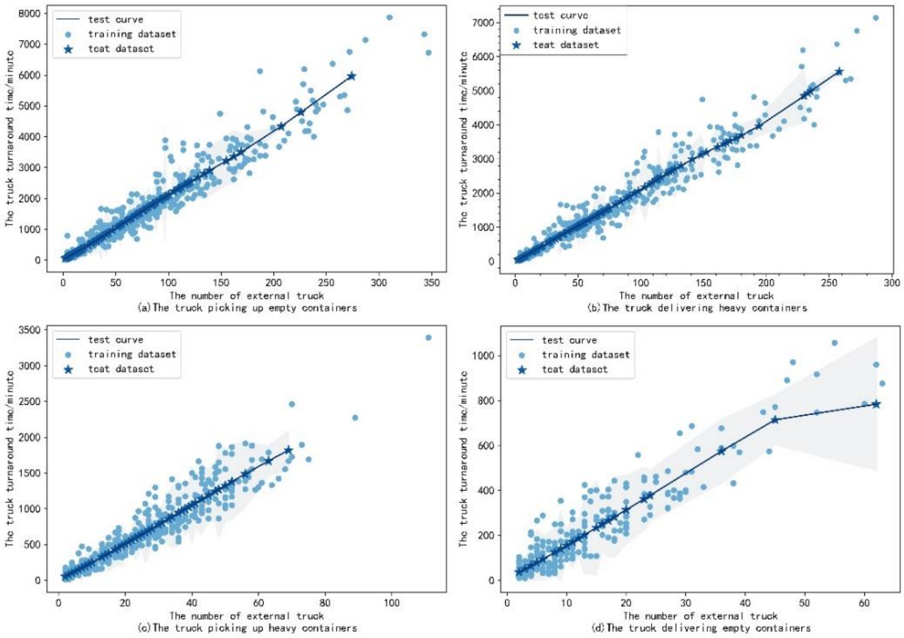

Figure 5: The relationship between the number of external trucks and the total truck turnaround time

Table 2. The prediction results of Gaussian process regression

Truck operation type	σ_f	l	R^2	*MAPE (%)*
picking up empty containers	0.312	54.63	0.98	4.93
delivering heavy containers	0.474	39.87	0.97	6.72
picking up heavy containers	0.261	10.63	0.98	4.68
delivering empty containers	0.914	21.87	0.97	7.71

The paper employs polynomial regression to compare the traditional parametric model with Gaussian process regression. The results of the polynomial regression are presented in Table 3. The Gaussian process regression results show a lower MAPE than the polynomial regression.

Table 3. The prediction results of polynomial regression

Truck operation type	*displayed formula*	R^2	*MAPE (%)*
picking up empty containers	$y = 0.007x^2 + 16.21x + 0.82$	0.94	7.46
delivering heavy containers	$y = 21.22x - 10.45$	0.96	8.42
picking up heavy containers	$y = 26.83x - 15.78$	0.97	8.83
delivering empty containers	$y = 0.011x^2 + 16.29x - 1.71$	0.96	8.18

4.2 The analysis of the dual-driven approach

This subsection takes the actual operation demand of the container terminal on a particular day as an example. Considering the arrival demand at midnight is low, the arrival number of external trucks in 12 periods from 9:00 to 20:00 is selected to validate the proposed dual-driven approach. The arrival number of external trucks picking up empty containers, delivering heavy containers, picking up heavy containers, and delivering empty containers is [955,355,249,102]. The maximum quota for operation type w is $[150, 40, 30, 20]$. The unit waiting cost c_w is $[1, 2, 2, 1]$ in RMB/minute, and the unit transfer cost α_w is $[60, 120, 120, 60]$ in RMB/minute. In order to emphasize the priority of heavy container operation, set the ratio of the cost of empty containers to that of heavy containers as $1:2$.

4.2.1 The results of the dual-driven approach

The results of the dual-driven approach are shown in Table 4. The results show that the dual-driven approach can reduce the total cost of each truck operation type. The total cost of the truck picking up empty containers is reduced by 10.33%; the total cost of the truck picking up heavy containers is reduced by 4.10%; the total cost of the truck delivering heavy containers is reduced by 2.66%; the total cost of the truck delivering empty container is reduced by 10.90%. The total truck turnaround time is affected by optimizing the period of the arrival of the truck through the truck appointment system, which can effectively reduce the waiting cost. The proposed method is more effective for optimizing the trucks picking up and delivering empty containers, which can reduce the cost by more than 10%.

Figure 6 shows the distribution of arrival periods for the four operation types of external trucks before and after optimizing the truck appointment quota. Considering the waiting cost and the transfer cost, optimizing the truck appointment system tends to smooth the arrival of trucks. This involves redistributing a large number of trucks that would have arrived in the same appointment period to other periods to achieve a balanced truck arrival across decision periods.

Table 4. The results of the proposed dual-driven approach

Truck operation type	*Pre-optimization cost/RMB*	*After-optimization cost/RMB*	*The number of transferred trucks*	*The deviation period/hour*
picking up empty containers	34,066	30,545	135	173
delivering heavy containers	33,834	32,448	32	36
picking up heavy containers	27,296	26,571	23	26
delivering empty containers	4,359	3,884	15	21

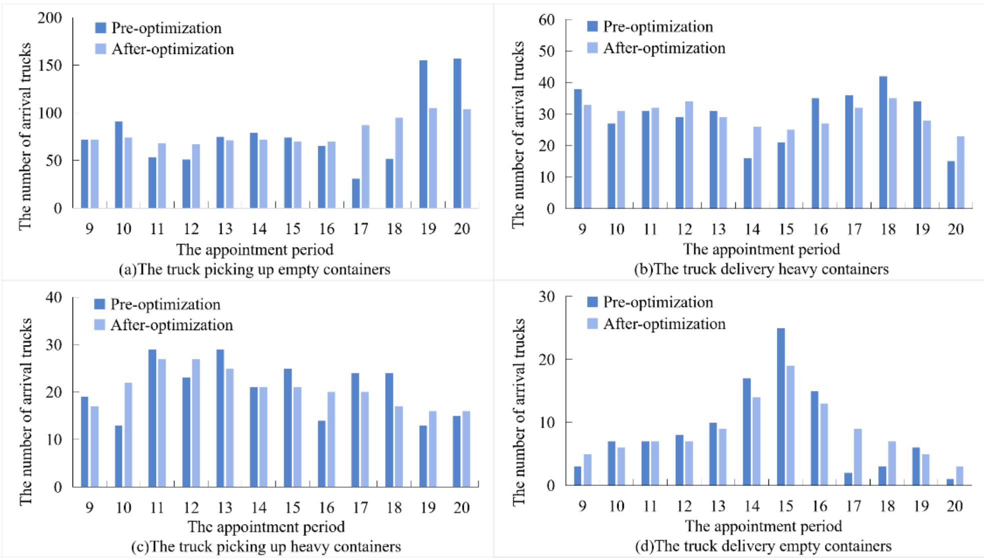

Figure 6: The respective appointment quota plans of four truck operation types

After the optimization of the truck appointment quota, the transfer number of the truck picking up empty containers is 135 units, accounting for 13.57%; the transfer number of the truck delivery heavy containers is 64 units, accounting for 9.01%; the transfer number of the truck picking up heavy containers is 23 units, accounting for 9.24%; the transfer volume number of the truck delivery empty containers is 30 units, accounting for 14.42%. The original arrival data of the truck delivery and picking up empty containers have apparent peaks and valleys. After optimization, the transfer number of the truck is about 15%. The arrival distribution of the containers is smoother, which leads to significant changes in truck turnaround time and a further reduction in total cost.

4.2.2 The analysis of results for the refined and unrefined truck operation types

Figure 7 shows the appointment quota plans for refined and unrefined truck operation types. In the traditional, unrefined truck operation types optimization, the relationship between the number of external trucks and the total truck turnaround time is analyzed for all operation types, and the regression results are $\sigma = 0.357, l = 34.26$, with MAPE of 10.46% and R^2 of 0.95. The total cost is reduced by 5,292 RMB in the traditional optimization, and the total transfer number of trucks is 110 units. For the optimization of refined truck operation types, the maximum and minimum appointment quotas are 154 units and 127 units. For the optimization of unrefined truck operation types, the maximum and minimum appointment quotas are 172 units and 97 units. Compared with the result of traditional optimization, the optimization result of the total cost of refined truck operation types can be further reduced by 5.31%.

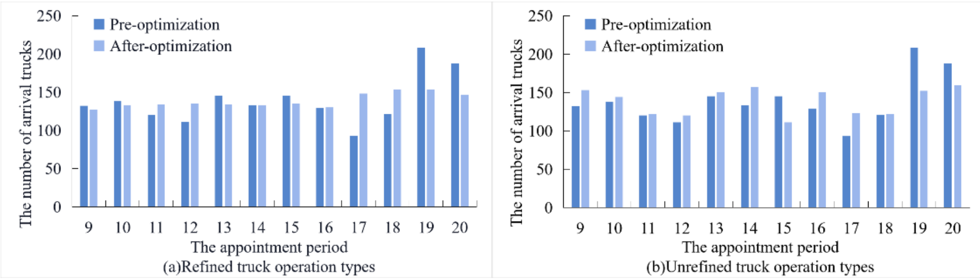

Figure 7: The appointment quota plans of refined and unrefined truck operation type

5. CONCLUSION

The paper establishes a dual-driven approach to optimize the truck appointment quota. The dual-driven approach combines Gaussian process regression and a programming model. The primary findings can be summarized as follows. Gaussian process regression is an effective approach for analyzing the relationship between the number of external trucks arriving and the total truck turnaround time using historical data. The results of Gaussian process regression have lower errors compared to polynomial regression. Compared to traditional optimizing the truck appointment quota, optimizing under refined truck operation types is more efficient, and the extreme of the truck appointment quota is smaller. The optimization is more efficient in empty container trucks compared to heavy container trucks. The truck appointment quota optimization model presented in this paper utilizes historical data to accurately illustrate the relationship between the number of external trucks and the total truck turnaround time.

6. ACKNOWLEDGMENTS

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