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Research on the Prediction of Quay Crane Resource Hour based on Ensemble Learning

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ABSTRACT

In Container terminals, a quay crane's resource hour is affected by various complex nonlinear factors, and it is not easy to make a forecast quickly and accurately. Most ports adopt the empirical estimation method at present, and most of the studies assumed that accurate quay crane's resource hour could be obtained in advance. Through the ensemble learning (EL) method, the influence factors and correlation of quay crane's resources hour were analyzed based on a large amount of historical data. A multi-factor ensemble learning estimation model based quay crane's resource hour was established. Through a numerical example, it is finally found that Adaboost algorithm has the best effect of prediction, with an error of 1.5%. Through the example analysis, it comes to a conclusion: the error is 131.86% estimated by the experience method. It will lead that subsequent shipping cannot be serviced as scheduled, increasing the equipment wait time and preparation time, and generating additional cost and energy consumption. In contrast, the error based Adaboost learning estimation method is 12.72%. So Adaboost has better performance.

1. Introduction

In recent years, with the continuous development of container terminals, terminal data has exploded, and the utilization rate of data is extremely low. Scholars begin to turn their attention to the analysis and application of port data^[2,3].

Vessel's handling time is a decisive factor in container terminals, which is closely related to the efficiency of port's service and cost of vessels. In the planning stage, the handling time is affected by various operating stages, such as berth allocation, quay crane allocation, quay crane scheduling, yard planning, etc. Vessel's handling time, usually as an important input to determine reliable plan, is

considered to be static (depending on the number of berth, number of quay crane, number of crane's move, etc.), but in practice there are many complicated factors, such as personnel, quay crane and truck, on its impact), will cause a deviation between the vessel handling time of the predicted value and the actual value, and could lead to congestion or even interruption in a port or other operations on the supply chain.

Vessel's handling time can be obtained by the quay crane number of each berth and the quay crane resource hour of each vessel (QC-hours, see Meisel and Bierwirth^[4]). The term "quay crane resource hour" refers to the amount of quay crane time resources occupied by vessel

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loading and unloading operations, which is expressed in hours. Compared with vessel's handling time, using QC-hours to measure the vessel's workload and serve as the input data of vessel operation plan can control the quay crane capacity more accurately, which is more conducive to the description and planning of quay crane resources by planners. However, in the current practical operation of ports, QC-hours are usually estimated by operators based on experience. The empirical estimation method cannot accurately grasp the nonlinear influence of multiple complex factors on QC-hours in each operation stage, which leads to frequent additional costs and energy consumption in the actual operation of the port. For example, the vessel operation is delayed due to the shortage of available quay crane resources; then, delay in vessel's departure from berth causes subsequent vessels to be unable to berth, and the operation plan should be adjusted temporarily; moreover, over-estimation of QC-hours required results in equipment ullage, etc.

The main objective of this paper is to investigate the method of QC-hours estimation through the effective use of port data, so as to obtain more accurate vessel's handling time, and then reduce the uncertainty of vessel operation plan, and improve its anti-risk ability and feasibility.

In this paper, the ensemble learning model is used to analyze a large amount of data from various operational stages in the container terminal operation system (TOS) and estimate QC-hours. Feature data that may affect QC-hours are extracted from different operational stages of the container terminal, and needs to be processed such as feature selection, data preprocessing and data set's conversion. In order to determine an appropriate modeling method, an empirical study related to the estimation of QC-hours in container terminals was carried out by comparing different evaluation indicators of various estimation methods, and the optimal estimation method with high accuracy and short calculation time was obtained.

The innovation points of this paper are as follows: (1) by studying the effectiveness of ensemble learning to estimate qc-hours in ports, it makes up for the lack of relevant empirical research, and provides a new research direction for the application of big data in smart ports.(2) The key factors affecting vessel handling in different operation stages of container terminals and the interrelations between these factors were systematically studied for the first time.(3) It upgrades the current resource estimation method in the port, which has reference significance for accurate control of port resources.(4) It provides a new research idea for anti-interference management of port operation plan.

2.Literature Review

The research object of this paper is the "quay crane resource" of container terminals. Due to the quay crane resources are mostly used in the field of vessel operation planning, so the references of this paper focuses on this field.

Usually, the operation of container terminals can be divided into the vessel operation process of container handling and the operation process of container receiving and transfer by the outward truck. Allocating resources and scheduling equipment for these operations has become a major planning problem for container terminals. Researchers have reviewed these issues in container terminal operations^[5-9].

In the operation planning of container terminals, vessel's handling time is a key factor, which is affected by various factors such as ship stowage plan, number of berth and quay crane and operation rules of quay cranes, etc. And its accuracy is related to the reliability of each operation plan. In general, it is difficult to predict the degree of influence of these factors on handling time, and inaccurate estimation results of handling time will lead to serious consequences: One side, over-estimation of time will lead to waste of resources in berths and cranes; In turn, under-estimation will cause delay to subsequent vessels. All along, relevant studies have been trying to solve this problem by constructing the combined framework of berth allocation, quay crane allocation and scheduling, or considering robustness in the model of vessel operation plan to improve the ability to cope with errors, such as Karam and Eltawil^[10], Xu, Chen and Quan^[11].But this approach does not improve the accuracy of time index.

The main equipment for handling operations is the quay crane. Meisel and Bierwirth^[4] first proposed the concept of "quay crane resource time" to refine the handling time and describe the vessel operation plan more accurately. Quay crane resource refers to the workload completed by a quay crane in one hour, and it is the quay crane operation time estimated in advance, that is, the quay crane capacity that a vessel needs to occupy. Accurate handling time can be obtained by QC-hours. In existing studies, QC-hours are assumed to be a known information^[1], which is mostly obtained from historical experience and personal experience of planners. In fact, due to the nonlinear influence of each port operation stage on the handling operation, the QC-hours obtained by empirical estimation tend to deviate from the actual value, so the estimation is highly uncertain and subjective, and the vessel operation plan based on it is often forced to be adjusted temporarily. When Bierwirth and Meisel^[12] summarized the container

terminal operation planning model, they also mentioned that QC-hour has an important influence on the time index in the integrated berth plan, but is often ignored by the relevant studies of QCAP. Therefore, scholars' research on interference management in the field of port planning is triggered. See HU, ZHANG and DING^[13].

The research method is ensemble learning method. Ensemble learning is a kind of data mining algorithm. In essence, multiple weak classifiers are transformed into a strong classifier through an effective integration, so as to improve classification accuracy^[14]. Dasarathy and Sheela first proposed the idea of Ensemble Learning in 1979^[15]. Since then, ensemble learning has developed rapidly, with more and more novel ideas and models appearing, and major breakthroughs have been made in many fields, such as time series analysis^[16] and medical health^[17]. These fields have similar characteristics, that is, the data dimension is high, the data structure is complex, the feature is fuzzy and the data analysis and processing by manpower is difficult and costly. The characteristic of maximizing learning ability by ensemble learning is well embodied in this kind of problem.

The differences between ensemble learning algorithms are mainly based on three aspects^[18]: the training data provided to individual learners, the process of generating individual learners, and the combination of learning results. According to the training method of the base learner, the ensemble learning algorithm can be divided into Bagging^[19], Boosting^[20], Stacking^[21]. There are two common combined strategies for base learner^[22]: voting method and average method. When applying the ensemble learning method, the suitable combination strategy should be selected according to the characteristics of the base learner.

According to the characteristics of multi-region interaction, high complexity and high feature dimension of port, Adaboost method^[23] with inherent feature selection and RF method with excellent generalization ability and random attribute selection function^[24] are selected. Meanwhile, Bagging, GBRT (gradient boosted regression trees)^[25] and SVR (Support Vector Regression) method^[26] are selected for comparison and validation.

3. Research Methods

The initial data for the research was collected from a large container terminal in Waigaoqiao, Shanghai, and was pre-processed. And then, the data set is divided into training set and test set. Based on the sorted data set, the initial models of RF and SVR are built on the training set by Python. The initial model with better imitative effect is selected, its parameters are adjusted, and the Adaboost, Bag-

ging and GBRT models are built respectively as the base learner. Parameters are adjusted to improve the accuracy of the ensemble learning model on the training set, and the performance of the model is evaluated using the test set. By modeling and analyzing the actual data, the feasibility and practical significance of the ensemble learning estimating QC-hours were explored.

3.1 Initial Data

There are 17,197 original data and 57 initial data features extracted from TOS, which are divided into four categories, including vessel data, quay crane operation data, yard operation data and horizontal transportation operation data.

The data are from TOS of a large container terminal in Waigaoqiao, Shanghai, and used for training learners. In fact, some of the data are posterior data (marked with “*”), and the accurate data cannot be known before the completion of the operation. However, such data is associated with QC-hours, so it is reserved to explore its influence on QC-hours.

3.2 Data Preprocessing

Actual data is often incomplete, and noisy. It is necessary to preprocess the original data in order to improve the quality of the data and improve the accuracy and efficiency of the subsequent process.

The pretreatment process is as follows:

3.2.1 Data Cleaning

The data cleaning process can fill in missing values, smooth noise, identify outliers, and correct inconsistencies in the data. For the missing values, it can be processed by functions in Python's NumPy library, and based on whether the data is skewed, the attribute mean is filled in for all samples. This study is aimed at the handling of containers after the berthing of self-sailing vessels in large container terminals, without considering the situation of barges. Furthermore, the number of data samples is relatively rich, so the sample with the outliers are deleted.

3.2.2 Data Conversion

By data conversion, data is transformed or consolidated into a form suitable for centralized processing. The nominal data and ID tags (such as the route name, the actual berthing position of the vessel, and the actual berthing direction of the vessel) are standardized by LabelEncoder function. The numeric data is standardized by the StandardScaler function.

3.2.3 Feature Selection and Result Analysis

By ranking the importance of features (i.e., ranking the contribution of each feature in the process of predicting QC-hours) and setting a threshold of importance, feature items with the least impact were screened out. The random forest method was used to rank the importance of features. The out-of-band data (OOB) error rate was used as an evaluation indicator to measure the contribution.

It is assumed that there are 1000 trees in the forest, and the importance of features is ranked from the largest to the smallest, as shown in Table 1. According to the order of features' importance, the three weak influencing features of "the minimum number of reposition containers with the yard crane for a vessel in one same bay", "the minimum workload of the yard crane for a vessel" and "the minimum number of yard crane" were deleted to improve the calculation efficiency. Among all the feature items, "quay crane movement number", "empty truck trip number", "yard crane workload for a vessel", "average quay crane number per hour" and "truck waiting time at quay crane" have the largest contribution, accounting for 98.79% of the total.

Table 1 importance ranking table of random forest features

Features	contribution	Features	contribution
quay crane movement number	0.683995	actual berthing direction of a vessel	3.55E-05
empty truck trip number	0.29398	the minimum number of reposition containers with	0
yard crane workload for a vessel	0.004841	the yard crane for a vessel in one same bay	
average quay crane number per hour	0.003358	the minimum workload of the yard crane for a vessel	0
truck waiting time at quay crane	0.001693	the minimum number of yard crane	0
total vessel workload on the seaside in the sametime (UNIT)	0.000807		
...	...		

In addition, We know from the sequence that posteriori features has certain contribution for the forecast of QC-hours, including "quay crane movement number" and "empty truck trip number" with the largest contribution while the rest of 8 posterior features have small contribution, in which "truck waiting time" (i.e., "truck waiting time at quay crane" and "truck waiting time at yard crane") is the relatively important features.

3.3 Building Model and Tuning Parameter

The model is built using functions in Python's Sklearn library.

The preprocessed data set was divided into training set and testing set in a ratio of 6:4. Because the sample number of data set is not large enough and there are many features, the proportion of testing set is increased to prevent over-fitting. In order to select a suitable base learner, the initial models of RF and SVR(Support Vector Regression) were built, and the scores (accuracy) of the two were calculated by 10 fold cross-validation. The testing results were as follows: the mean value of RF score was 0.9840 and the standard deviation was 0.0038. While, the mean value of SVR score was 0.9772 and the standard deviation was 0.0068.

By comparison, RF performs better than SVR as a base learner. Cross-validation is a good way to evaluate the generalization ability of a model, whose purpose is to select different model types rather than to obtain specific parameters of the model.

Furthermore, the parameters of RF and SVR base learner are tuned. The random search parameter tuning method is adopted here. The search ability of random search depends on the number of training iteration. The higher the value, the greater the parameter accuracy, but the longer the search time.

Bagging algorithm, Adaboost algorithm and GBRT algorithm are built with the RF base learner after tuning. The parameter Spaces before and after tuning are shown in Table 2.

Table 2 parameter space of ensemble learning models

model	parameter	Before tuning	After tuning
Bagging	n_estimators	20	65
	max_samples	15	135
	warm_start	False	False
	bootstrap	True	True
Adaboost	n_estimators	20	25
	loss	"linear"	"exponential"
GBRT	learning_rate	0.8	0.5544
	max_depth	15	11.3219
	n_estimators	20	150
	warm_start	False	<class "bool">
	min_samples_leaf	1	60
	max_features	None	"auto"

4. Results and Evaluation

Above all, RMSE(Root Mean Squard Error) and Adjusted

R-squared Error were selected as the evaluation indicators for the above five models to make an unified evaluation.

(1)RMSE: Root Mean Square Error is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are.

$$E(f; D) = \sqrt{\frac{1}{m} \sum_{i=1}^m (Y_{\text{actual}} - Y_{\text{predict}})^2}$$

(2)Adjusted R Squared: A penalty is added to R^2 for additional variables that will not improve the effectiveness of the model.

$$R^2_{adj} = 1 - \left[\frac{(1 - R^2)(n - 1)}{n - p - 1} \right]$$

Where: N -- sample size; P -- Number of features
The evaluation results are shown in Table 3.

Table 3 evaluation results of each model

model \ result	tuning	RMSE	Adjusted R Squared
RF	-	0.1215	0.9847
SVR	-	0.2209	0.9493
Bagging	before	0.5568	0.6778
	after	0.1427	0.9788
Adaboost	before	0.1186	0.9854
	after	0.1183	0.9855
GBRT	before	0.152	0.976
	after	0.1442	0.9784

According to the evaluation results of the model before and after parameter tuning, tuning parameters has the greatest impact on Bagging model, while the scores of Adaboost model and GBRT model are slightly improved. Among the five type of ensemble learning models, RF regression model and Adaboost regression model have the best prediction effect, and among which, Adaboost model has better prediction accuracy than RF, but its calculation cost is higher.

The fitting effect of Adaboost model on the testing set is shown in Figure 1. Sample points are clustered near the reference line, and the closer the position is to the reference line in the smooth scatter diagram, the darker the color is. The residual analysis of Adaboost model is carried out, and the residual histogram is shown in Figure 2. It can be seen that the residual distribution of Adaboost

model on the testing set basically conforms to the normal distribution.

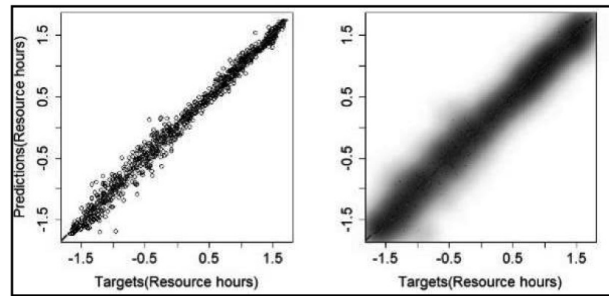


Figure 1 the fitting effect of Adaboost model on the test set

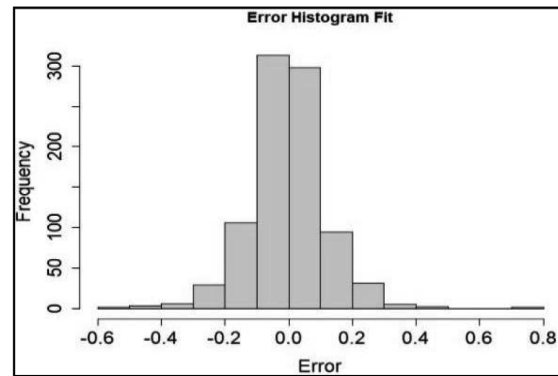


Figure 2 residual histogram of Adaboost model

To sum up, the fitting effect of the model meets the expected requirements.

5. Example Analysis

This section describes how to use the Ensemble Learning to predict the quay crane resource of a certain container terminal of Waigaoqiao in Shanghai. And analysis data is taken from on a certain day in 2017. The port has continuous berths, and 4 quay cranes are arranged along the selected shoreline. The arrival vessel information and estimated QC-hours data are as shown in Table 4. The empirical estimate of QC-hours in the table is the current customary method in ports. According to the statistics of the quay crane working efficiency data of the port over a period of time, the general QC efficiency of the port in a certain period can be obtained: 33TEU/h for empty containers, 25TEU/h for full containers, 6TEU/h for dangerous goods containers, and 27TEU/h for special and refrigerated containers. Combined with the number of container, QC-hours can be estimated by the empirical method.

The MRE (Mean Relative Error) between QC-hours estimation and actual value obtained by the two methods is as follows: the empirical estimation method is 131.86%,

Table 4 statistical table of arrival ship information

index	name	Estimated time of arrival	Minimum QC number	Maximum QC number	QC-hours (empirical estimate)	QC-hours (model prediction)	QC-hours(Actual value)
1	inland river	2017/12/27 1:00	1	1	1.44	1.38	0.93
2	CHJ-JIHA	2017/12/27 1:10	1	2	5.56	9.51	10.78
3	CHJ-JIHA	2017/12/27 2:10	1	1	10.96	7.96	8.54
4	YSK-XXX	2017/12/27 3:40	1	1	8.66	7.66	5.80
5	CHJ-JIHA	2017/12/27 10:15	1	1	4.88	5.20	4.85
6	CHJ-XXX	2017/12/27 10:07	1	2	2.55	5.43	5.00
7	CHJ-XXX	2017/12/27 16:00	1	1	3.34	3.80	3.91
8	CHJ-WYCJ	2017/12/27 16:00	1	1	4.04	6.88	5.97
9	CHJ-XXX	2017/12/27 16:30	1	1	0.56	5.73	5.11
10	CHJ-XXX	2017/12/27 20:00	1	1	3.52	3.50	3.72
11	CHJ-XXX	2017/12/27 20:45	1	2	1.27	5.78	4.93
total	-	-	-	-	46.78	62.84	59.52

and Adaboost is 12.72%. The results show that the error between the value predicted by the empirical method and the actual value is too large.

According to QC-hours and available quay cranes, the berth planning Gantt chart can be drawn as shown in Figure 3 in combination with ship type, ship stowage plan and expected berth position(the berth that minimizes the operating cost on the landside), which shows that: the berths allocated in Figure 3a are distributed in a fragmented shape. The berths allocated in Figure 3b show a continuous and clustered distribution, which is more in line with the arrival and departure times of ships in the actual situation.

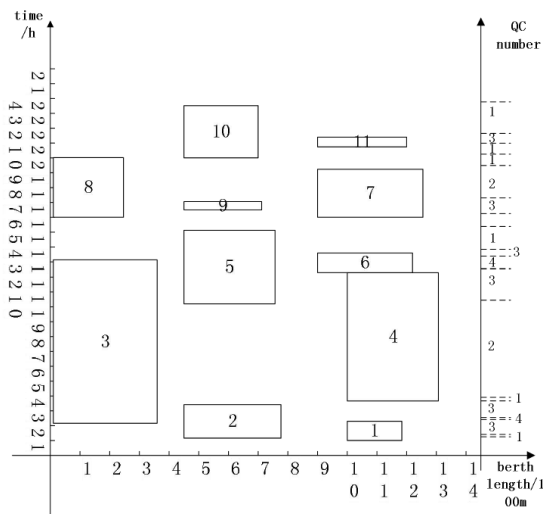


Figure 3a. Berth allocation diagram based on empirical estimation

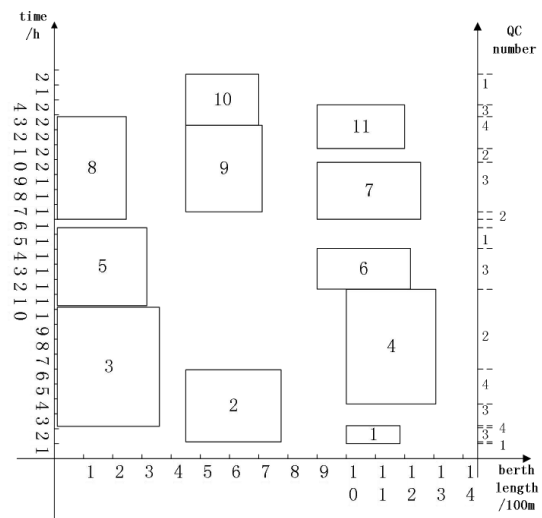


Figure 3b. Berth allocation diagram based on Adaboost method

The comparison shows that: (1) over-forecast of qc-hours (ship 2,3) will generate additional QC preparation/depletion costs, which will lead to subsequent ships not being able to dock at the expected berths, and increase the operating costs on the landside; (2) under-forecast (ship 10) will cause subsequent ships to be unable to dock/leave as scheduled;(3) frequent starting, stopping equipment will increase the operating cost of equipment and exacerbate the ullage of the units life. As shown in Figure 3a, due to the large QC-hours prediction deviation, QC will frequently carry out intermittent operations. In addition, excessive prediction deviation leads to insufficient capac-

ity of pre-prepared equipment in ports, which increases ship berthing time, equipment energy consumption and scheduling operation.

To sum up, the current estimation method of QC-hours in ports is too rough, ignoring the impact of facilities and equipment in each stage of operation on QC efficiency. The large deviation from the actual situation will result in waste of equipment capacity, increase of port operation cost and extra energy consumption, and increase the probability of congestion. Using ensemble learning method to predict QC-hours will effectively improve the above problems.

6. Conclusion

Aiming to estimate QC-hours, an ensemble learning estimation model based on random search parameter optimization was proposed. The optimal model of the estimation task was determined by comparing the evaluation indicators of various models. The model evaluation results show that Adaboost has the best prediction effect. The study found five features have the most considerable contribution within 57 features, accounting for 98.79% of the total.

Besides, the study also shows that ensemble learning is suitable for data mining in ports. The forecast model can help the staff accurately control port resources, be better able to complete agreement with the shipping company about time, resources, and other service requirements. At the same time, significantly optimize unreasonable steps in port management and planning, reduce workload, improve the port productivity and serviceability, give full play to the port of each operation stage cooperation ability, and strengthen the port resource integration. Simultaneously, the method of data analysis was proposed to optimize the accuracy of the time index, which provides a new idea for research in interference management.

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