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ESTIMATING CONTAINERSHIP HANDLING TIMES IN A CONTAINER TERMINAL*

コンテナターミナルにおけるコンテナ船の荷役作業時間推定モデル

By Etsuko NISHIMURA**, Akio IMAI***, Bai ZHAO**** and Hitoshi KANEKO*****
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1. Introduction

In major ports in Japan and the U.S. such as Kobe, Yokohama, Los Angeles and Oakland, shipping lines lease the container terminals (referred to as Dedicated Terminal, DT) in order for them to be directly involved in the processing and handling of the containers as they aim to achieve higher productivity and economies of scale. Whereas this may be warranted in the case of a firm that handles a large amount of containers with a corresponding number of ship calls, it may not be justified if these quantities are not sufficient, as it will have an adverse effect on costs. Over the past several years, port charges in Japan have been consistently higher than those in other major ports. One of the reasons cited for the increased costs is the over-investment in ports with relatively small cargo volume.

A Multi-User Container Terminal (MUT) may be defined as a terminal with a long berth that is able to serve several ships simultaneously, which are dynamically allocated to the berth and are not always assigned to specific berth locations. Some major container ports provide MUTs, while most of them feature DTs. Examples of the MUT are Hong Kong International Terminal (HIT) in Hong Kong, Pusan East Container Terminal (PECT) in Pusan, and Delta Multi-User Terminal (DMU) in Rotterdam. In addition, most container terminals in China are used as MUTs, since the limited terminal space due to a smaller construction budget has to be utilized efficiently in order to meet the huge container traffic flow. The MUT may dramatically save costs in handling less container traffic in ports of Japan.

In an MUT, both deep-sea vessels and short-sea feeders are served together; therefore transshipped containers are typically stored far from berth locations of connecting ships. The efficient berth scheduling for the MUT has been analyzed in Imai et al.[2), 3)] and Nishimura et al.[7)] by which, the handling time for a particular ship is assumed to depend on its berth location and container-stack location in the yard, without considering the details of terminal activities. For more realistic assumptions in those berth scheduling studies, this paper develops statistical models to estimate the handling time spent by ships in port.

2. Ship handling simulation

The main purpose of this study is to examine how the ship handling time depends on the geographic relationship between the ship location in the quay and the container-stack location in the yard. For this, we need a handling time data set when a particular ship is moored at a certain berth location and the ones when it is moored at some other locations. However, it is costly and even impossible to collect such statistics by changing ship's berthing locations physically in a busy container terminal. Thus, we alternatively develop a model that simulates complicated activities of various types of equipment being involved in handling operations in an MUT. By conducting a number of computational experiments, we observe handling activities and collect statistics, by which we develop mathematical models that estimate the containership handling time.

(1) Outline of the handling simulation

The efficiency of a marine container terminal depends on the smooth and efficient handling of containers. There are

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three basic types of container handling systems engaged in loading and discharging operations in a container terminal: chassis, straddle-carrier and yard crane systems, the latter being the most popular in major terminals due to the need for high container-storage capacity in the yard. In this study, we assume a container terminal with yard cranes. For the yard crane system, there are several types of handling equipment employed such as quay cranes (QCs), yard cranes (YCs) and yard trailers (YTs).

In such a terminal, two types of operations are undertaken: loading and discharging ships, and handling delivery trucks that come to the terminal from hinterlands. For the efficient yard operation, the entire container storage is divided into two parts: one for import and the other for export. Each part consists of several blocks that are arranged by the voyage, so that the traffic of delivery truck is unlikely to interfere in loading and discharging tasks of ships. This enables us to put only handling activities of ships into the simulation model to get the statistics of the ship handling time. In practice, the damage check of container is conducted when the delivery trucks go through the gates. However, in this study, we do not take into account operations relevant to delivery trucks.

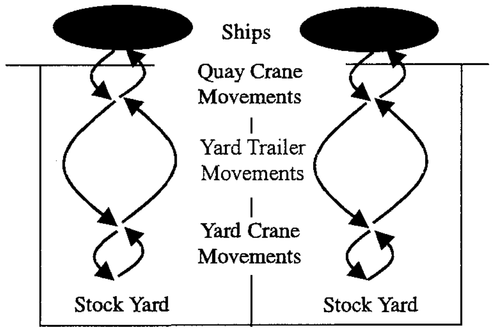


Figure 1. Handling cycle for machines

Figure 1 illustrates cycles of operations of QCs, YCs and YTs being engaged in handling ships. In the discharging operation, QCs move containers from ships to YTs, while YTs carry containers from the ship-side to YCs in storage areas. YCs move containers from YTs to container blocks. The loading operation will be carried out in a reverse order after discharging.

The number of QCs assigned to a ship depends on its handling volume. In principle, two YCs will be assigned to the handling job of containers by a QC. Four YTs are engaged in the container delivery to the storage area from a QC, each operating a shuttle service between a QC and a YC.

(2) Simulation model

The simulation model of the handling operation is implemented by a commercial simulation tool for discrete systems, AutoMod, which deals with both physical and logical elements of a system. AutoMod offers advanced features allowing users to simulate complex movements with consideration of the velocity of handling equipment such as QCs and YCs.

The model mainly consists of three components: ship arrival/departure sequences, discharging ships and loading ships. The entire process is as follows: A present job state of QC j at berth i is denoted by a variable $g(i, j)$ ranging from 0 to 2. A value 0 defines QC j at berth i without handling tasks, whereas values 1 and 2 imply discharging and loading states, respectively. A present job state at berth i is denoted by a variable $f(i)$ having 0 or 1. A value 0 defines no ship moored at berth i and consequently results in no handling job, whereas a value 1 implies discharging or loading state. As the variables are global, i.e., they are independent from any simulation tasks involved in the system, any states of events in the simulation run can be monitored whenever the values of the variables change.

Ship arrival is assumed to follow the exponential distribution.

The following is the detailed simulation procedure:

Step 1. Set the simulation run time. Let $f(i)$=0 for all the berths, and set $g(i, j)$=0 for all QCs.
Step 2. Keep looking at all QCs at all the berths until one of them makes a change in the handling state. Thereafter, if there is an empty berth ($f(i)$=0), go to Step 3. If QC j at berth i changes its handling job from discharging to loading, go to Step 5. If QC j at berth i completes the handling for a ship, go to Step 6.
Step 3. If no unprocessed ships are available, go to Step 4. Otherwise, get a ship to start its discharging at empty berth i, setting $f(i)$=1 and $g(i, j)$=1 for all QCs at berth i. Go to Step 2.
Step 4. If no ships are being processed in the terminal, stop the simulation. Otherwise, go to Step 2.
Step 5. Set $g(i, j)$=2 and go to Step 2.
Step 6. Set $g(i, j)$=0. Set $f(i)$=0 if a ship at berth i completes the handling and departs from the terminal ($g(i, j)$=0 for all QCs at berth i). Go to Step 3.

(3) Assumptions for simulation

We conduct numerical experiments by the simulation model for the following two cases:

Model A : Two-berth simulation
Model B : Four-berth simulation

The input data used in the simulation contain the handling time for machines (QC and YC) and the interval of ship arrival. The distributions for those were obtained through our survey in the port of Kobe. Ships arrive with an exponential interval and the machine handling time per container follows *k*-Erlangian and normal distributions as shown in Table 1. YTs run straight at 15 km/h and turn at 5 km/h. When passing each other, they slow down.

The number of containers loaded to and discharged from a ship ranges from 300 to 500, following a uniform distribution. Two QCs are engaged in loading and discharging containers to and from a ship, sharing containers evenly. Containers for each ship are stored at arbitrary stack areas.

(4) Verification of the reappearance of actual situation

To verify the reappearance of actual handling situation, we compare the handling time obtained by simulation with actual handling time data from the handling with two berths in the port of Tokyo under the same condition in terms of the number of QCs and YTs, the number of containers and the storage pattern of containers for target ships.

Figure 2 shows the handling times from the actual data and those from the simulation model, whereas Table 2 reveals the number of machines and the number of handling containers for target ships. The percentage shows the error between actual handling times and those computed by simulations, which is defined as:

Table 1. Distribution functions for container handling machines

	Full container		Empty container	
	k	Avg (min.)	*k*	Avg (min.)
Discharging by QC	16	0.8	15	0.7
Loading by QC	Normal	0.8	35	0.6
YC	19	1.2	6	0.9

Table 2. Number of machines and handling containers for target ships

	Ship name					
	AM	AR	EM	AC	TK	SE
Number of QCs	2	2	1	2	1	2
Number of YTs per QC	4	3	4	4	4	4
Number of Containers	366	318	79	408	42	410

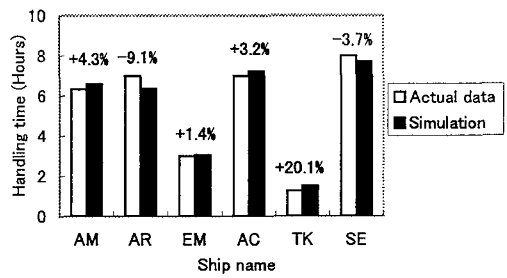


Figure 2. Verification of the reappearance of actual situation by simulation model

$$Error(\%) = \frac{\text{Simulation output} - \text{Actual data}}{\text{Actual data}} \times 100 \tag{1}$$

Except for ship TK, the error is less than 10%. For ship TK, the gap in time is 15 minutes. Those errors are relatively small; therefore, the simulation model reflects the actual situation.

3. Estimating the ship handling time by multiple regression model

By the ship handling simulation, we are able to measure the time spent in a handling operation of a particular ship. With all the handling times observed for the ships involved in the system, we develop a multiple regression model that estimates the handling time, taking into account the factors that might influence on the time.

(1) Data

We provided ten different seed sets for random numbers to generate the ship arrival and machine cycle times without wait. The number of YTs assigned to one QC ranges from 1 to 5. The terminal operation is simulated for three days.

Having chosen the handling time as the dependent variable and the following three elements as independent variables: the number of containers handled for a ship, the number of YTs, and the distance between the ship location in the quay and its dedicated container storage area in the yard, we performed the multiple regression analysis.

(2) Multiple regression model

From some case studies, the best coefficient of determination is obtained and the results of *t*-test and *F*-test are significant at a 0.05 level, when all the variables are logarithmically transformed. Those results are shown in Table 3.

The coefficients of determination for models A and B are 79% and 88%, respectively. The *F*-value is more than 2.605 for both models. For both models, the partial regression coefficient for the number of containers handled is positive, while the one for the number of YTs is negative. Thus, the time increases as more containers are handled and less YTs are employed. This result seems appropriate.

The partial regression coefficient for the distance between ship and container locations is positive for both models, justifying the models. The value of partial regression coefficient for model A, however, is nearly zero; therefore the distance has a small influence on the time. The value for model B is greater than for model A. The reason is that as model B has more berths than model A, longer trips of YTs are very likely.

Table 3. Estimating handling time by multiple regression model

Dependent variable y: Ship handling time				
		Independent variables	Partial regression coefficient	*t*-value
Model A	R^2 0.791	Constant	2.79	5.82
Degrees of freedom 593		x_1	0.79	9.81
	F-value 695.8	x_2	-0.60	-44.62
		x_3	0.01	0.29
Model B	R^2 0.879	Constant	1.71	2.31
Degrees of freedom 894		x_1	0.75	6.20
	F-value 458.2	x_2	-0.77	-40.84
		x_3	0.29	16.78

x_1 : Number of containers handled, x_2 : Number of YTs,
x_3 : Distance between ship location and container stack

The *t*-values for the number of containers and the number of YTs are greater than 1.645 and the result of *t*-test is significant at a 0.05 level. The *t*-value for the distance in model A is less than 1.645 and the result of *t*-test is not significant at a 0.05 level. However, the result of *t*-test in a larger terminal, i.e., model B, is significant at a 0.05 level.

4. Estimating the ship handling time by the neural network

In a DT, a set of YTs is usually assigned to a specific QC until the work is finished. However, another assignment seems advantageous: a trailer comes to a container-stack point in the yard after receiving a container from a QC, then it goes to the next stack point to receive a container for export and proceeds to another QC under loading operation. Such a dynamic YT routing may reduce the YT fleet size without increasing the entire dwell time of ship in port. Nishimura et al.[8] propose the dynamic YT operation in an MUT. In the dynamic YT allocation they proposed, if a ship is allocated to a quay location far from its container storage, YTs might be assigned to some sophisticated tours with a different itinerary. Consequently, the regression model may not be adaptable for the dynamic YT assignment, especially in the case of the multi-trailer system where a container does not necessarily travel directly from its ship to the allocated storage, and vise versa. Therefore, the travel time may not have a positive association with the direct distance between the ship location and the containers storage.

In order to cope with the above issue, we next develop another estimation model by employing the neural network, which is widely applied for the optimization and pattern recognition problems. Predictive skills of the neural network and the multiple regression models are compared using outputs of simulation model B. We examine the neural network model by comparisons between the neural network and the multiple regression models in terms of estimation quality.

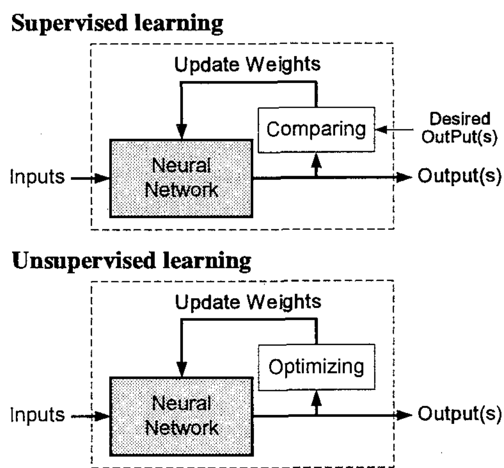


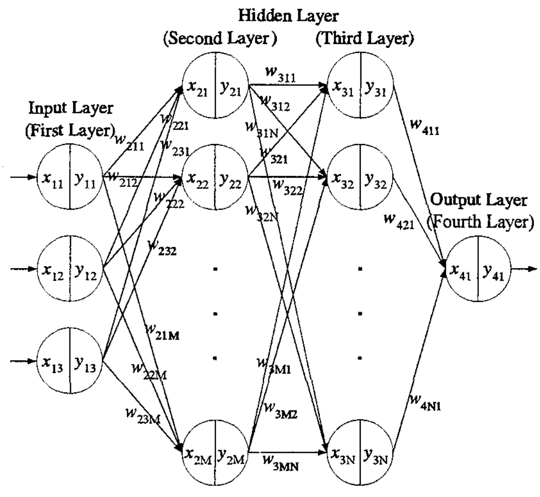
Figure 3. Neural network learning

(1) Neural network approach

Neural networks are different from conventional programs in the sense that they learn to solve programs. Learning in neural networks takes place by adjusting weights such that the final set of weights can map inputs to the output(s). As shown in Figure 3, there are two ways of adjusting the weights: the supervised and unsupervised. In the supervised learning, the network is presented with both inputs and desired outputs. Therefore, the network can compare its results with the desired outputs and minimize the error. In the unsupervised learning, the outputs are not defined and the network tries to classify the inputs according to the features inherent in the inputs. Supervised neural networks are the most common for the time series prediction.

Neural networks can also be classified according to the direction of information flow from the input layer to the output layer. This flow is either feed-forward or feed-forward and feed-backward. The latter is called "bi-directional" or "recurrent". In bi-directional networks, the states of neurons are simultaneously determined. On the other hand, in feed-forward networks, the inputs are fed into the network and the output is determined in passing through the system.

Figure 4 illustrates the feed-forward network used in this study. The neural network model we propose consists of three input units: two hidden layers and one output unit. Input signals correspond to three variables: the number of containers, the number of YTs and the distance between the ship location and container storage. The model, therefore, has three neurons in an input layer.



x_{tj} : Input to jth neuron in tth layer
y_{tj} : Output from jth neuron in tth layer
w_{tij} : Weight vector connected between ith neuron in t-1th layer and jth neuron in tth layer

Figure 4. Feed-forward network model

Input variables for each layer can be defined as follows:

$$x_{tj} = \begin{cases} I_j, & \text{if the } t\text{ th layer is an input layer} \\ \sum_{i \in NR_t} w_{tij} y_{t-1i}, & \text{otherwise} \end{cases} \tag{2}$$

where I_j is the input to the jth neuron, and NR_t represents the neuron set on the tth layer. In Figure 3, the inputs are weighted and sent to the processing neurons in the next layer. At the processing stage, each neuron sums its weighted input, and classifies it according to a transfer function and then sends its output to all hidden neurons in the next layer.

During the training stage, the back propagation calculates the differences (errors) between the actual outputs and the target samples, and then it propagates back these errors from the output layer down to the input layer.

The total squared error can be described as

$$E_p(w_{tij}) = \frac{1}{2}(O_p - D_p)^2 \tag{3}$$

$$E(w_{tij}) = \sum_{p \in DT} E_p(w_{tij}) \tag{4}$$

where the index p ranges over the set of input and target pattern pair, O_p denotes the actual output value y_{41} for data pattern p, D_p the pth target pattern, $E_p(w_{tij})$ the error on data pattern p, DT the data pattern set, and $E(w_{tij})$ the total error of the entire set for data pattern.

The network uses this error information to organize its weights. Thus, the training's objective is to minimize the total of squared differentials between the actual outputs and the targets by modifying the weights.

(2) Back propagation learning algorithm

The back propagation feed-forward networks [1] with supervised learning rules are the most popular and useful for time series forecasting. The back propagation calculates the error signals from the last layer by back propagating them along a path of the steepest decent in the network. There are several ways of adjusting the weights based on the above calculated network errors. The back propagation employs an optimization method called the gradient descent method mapping the inputs to the outputs. The learning rule employs a back propagation procedure to update the weights.

The learning rule is defined as:

$$w_{tij}^{(r+1)} = w_{tij}^{(r)} - \eta \frac{\partial E_P(w_{tij})}{\partial w_{tij}}\bigg|_{w_{tij}=w_{tij}^{(r)}} \tag{5}$$

where η is the learning rate and r is the training cycle.

The change vector in the weight between neurons i and j could be expressed as follows:

$$\frac{\partial E_p(w_{tij})}{\partial w_{tij}} = -\delta_{tj} y_{t-1i} \tag{6}$$

If the tth layer is an output layer,

$$\delta_{tj} = -(y_{tj} - D_p)\frac{\partial y_{tj}}{\partial x_{tj}} \tag{7}$$

and if the tth layer is a hidden layer,

$$\delta_{tj} = \frac{\partial y_{tj}}{\partial x_{tj}} \sum_{k \in NR_{t+1}} \delta_{t+1k} w_{t+1jk} \tag{8}$$

where k represents the neuron in the (t+1)th layer.

The change of δ_{tj} can be calculated backwards by the back propagation using eqs.(7) and (8). Weight vector w_{tij} is updated by eq.(5). Various successful applications using this method have been reported.

(3) Learning parameters

All data sets are normalized into analog (0-1) or binary (0/1) type. This is necessary, since every neuron in the hidden and output layers of the back propagation employs a transfer function ranging from 0.0 to 1.0. The normalization is done by the following equation[4]:

$$A = \frac{B - B_{\min}}{B_{\max} - B_{\min}} \tag{9}$$

where B is a raw data set and A is a normalized input.

There are nine and 17 neurons in the second and third hidden layers, respectively. Learning rate η is set to 0.9. The initial weights for each network layer are generated by a uniform distribution ranging from −1.0 to 1.0. The network is trained by randomized starting weights for a maximum of 10,000 iterations.

The sigmoid functional form, which is the most popular for time series forecasting, is used as the transfer function. The sigmoid function is defined by eq.(10).

$$y_{tj} = \begin{cases} x_{tj}, & \text{if the } t\text{th layer is an input layer} \\ \dfrac{1}{1+\exp(-x_{tj})}, & \text{otherwise} \end{cases} \tag{10}$$

Then, $\frac{\partial y_{tj}}{\partial x_{tj}}$ in eqs.(7) and (8) is transformed to eq.(11)[4)-6)].

$$\frac{\partial y_{tj}}{\partial x_{tj}} = y_{tj}(1 - y_{tj}) \tag{11}$$

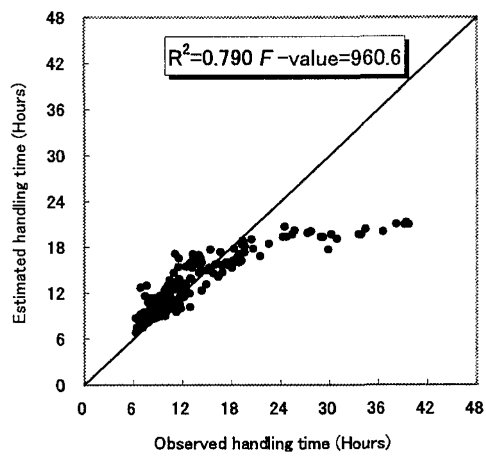


Figure 5. Correlation between observed and estimated handling time by neural network with training data

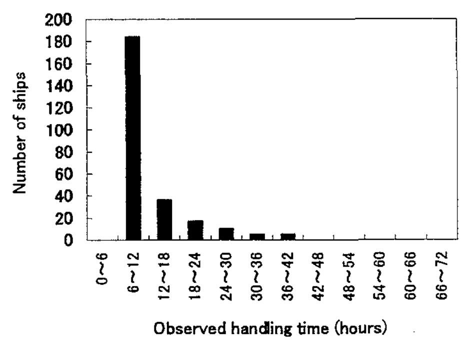


Figure 6. Number of ships in training data

(4) Training results

The neural network model was coded by C language on a SUN SPARC-64GP (275MHz) workstation and was linked with the output of the terminal handling simulation in order to train the network.

There is a data set stretching over three days that represents a continuous updating of the learning phase. In order to estimate the handling time, we use two training data sets generated by different seeds.

Figure 5 illustrates the correlation between the estimated and observed handling times, showing the effectiveness of the proposed neural network model. The estimated time tends to be a little shorter than the observed time. There is a big gap between them, especially when the handling time is long. Figure 6 shows the number of ships in training data by class of handling time with an interval of 6 hours. There are fewer ships with the handling time over 30 hours. The relative frequency of this class accounts for roughly 10%. This may result from few observed measurements in this class of the handling time.

The coefficient of determination R^2 is 79%. The F-value is greater than 3.84 and is significant at a 0.05 level.

(5) Comparison between the multiple regression and neural network models

With the weights obtained in the neural network learning, we compare the result of the neural network model with that of the multiple regression model B.

The regression formulation is as follows:

$$\ln y = 1.71 + 0.75 \ln x_1 - 0.77 \ln x_2 + 0.29 \ln x_3 \quad (12)$$

In order to calculate independent variable y, we transform eq.(11) to get eq.(12).

$$y = e^{1.71} x_1^{\,0.75} x_2^{\,-0.77} x_3^{\,0.29} \quad (13)$$

Figure 7 demonstrates the associations between the estimated and observed handling times by both the multiple regression and neural network models.

The coefficients of determination for the regression and neural network models are as high as 87% and 77%, respectively. Both F-values are greater than 2.605 and are significant at a 0.05 level. Observing these consequences, it is concluded that the neural network model is fairly good, although the regression model outperforms it. This encourages us to consider a neural network model to estimate the handling time in the dynamic YT assignment as mentioned before.

Figure 8 illustrates the number of ships in various classes of the handling time in experimental data. There are few ships with the handling time over 30 hours, which accounts for approximately 4%. This may result from few observed measurements in this class of the handling time like the training data.

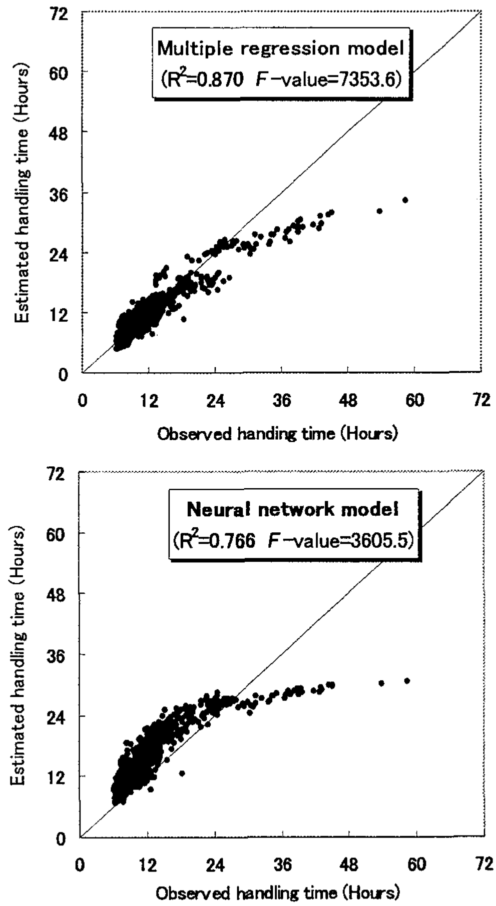


Figure 7. Comparison between multiple regression and neural network models

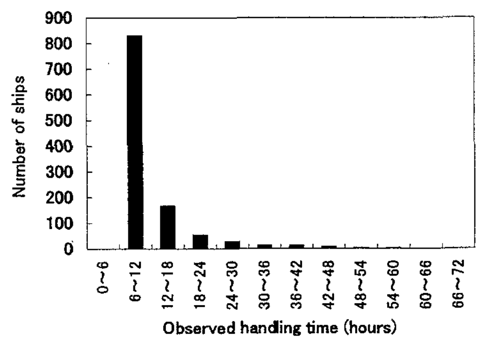


Figure 8. Number of ships in experiment data

5. Conclusions

In this study, we developed two models to estimate the containership handling time in a terminal. Due to the lack of observed handling times, for the estimation analysis, in a lot of different berth scheduling scenarios, we developed a simulation model of yard operations that produced the pseudo handling time, which could be used as an alternative of the observed handling time. The past berth allocation problems employed artificial handling times as the input to the problem concerned. We can obtain a more reasonable solution to the berth allocation problem with more realistic handling times that are defined by the estimation models we developed.

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Port charges in Japan have been consistently higher than those in other major hubs over several years. Part of the increased costs is the result of overcapitalization to the port for the relatively small cargo volume. For terminal efficiency, we have already investigated the dynamic berth allocation in a multi-user terminal, where the handling time of a ship is assumed to depend on its quay location and container stock location. However, the time is given in the berth allocation model without considering sophisticated operational aspects in the terminal. In this study, we construct models that estimate the ship handling time.

コンテナターミナルにおけるコンテナ船の荷役作業時間推定モデル

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日本の主要コンテナ港はアジアの競合港の出現に伴ってハブ機能が低下しているが、その要因に日本の高い港湾関連コストが挙げられる。我々は、船会社へのバースの専用貸しではなく、各船がどのバースででもサービスを受けることができるような複数バースの共同利用方式を提案しており、すでに効率的な船の係留バース決定方法を検討している。しかし、このバース決定問題ではターミナル内のオペレーションの詳細は考慮しておらず、バース決定に必要となる船の荷役時間へのターミナル作業の混雑状況や荷役機器の台数等の影響は検討していない。本研究では荷役機器の台数等を考慮した、コンテナ船の荷役作業時間予測モデルを開発する。
