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PREDICTION OF THE QUAY CRANE'S HANDLING TIME WITH EXTERNAL HANDLING FACTORS

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Abstract. *In container terminal, the number of containers handled per hour by the terminal is called productivity. Productivity in the container terminal is an important indicator that represents the terminal's capabilities of handling cargos. Although productivity can be improved by means of expanding the physical facilities of terminals (e.g., by adding additional equipment), these physical improvements involve huge investment costs, and most container terminals strive to improve productivity through improvements in their operational plans and operational methods. For operating plans and methods effectively, planning the quay crane scheduling is significant because it has a direct influence on minimizing the vessel's stay time in the port. It suggests that predicting the quay crane's working time may be closely associated with the container terminal's productivity. In our paper, we propose a new method of predicting the quay crane's working time by implementing the meaningful external factors of the quay crane and applying these impacts in the multi-layer perceptron model to predict the quay crane's handling time. With an advanced method of calculating the quay crane, our approach outperforms by reducing error up to 54% compared to the conventional method which measures unloading containers for one and a half minutes and loading containers for two and a half minutes.*
Keywords: Container terminal, Quay crane, Operational method, Bay clusters, Bootstrapping, Multi-layer perceptron, New quay crane working time

1. **Introduction.** Rapid trade volume growth suggests that the demand for merchandise from worldwide keeps growing, and shipping facilities' role is getting more significant [1]. The emergence of large container vessels has enlarged the shipping space available from the past and the container terminal's role also became prominent [2]. Container terminal puts lots of effort into operating the system in the most effective ways, such as predicting the vessel's arrival time to solve the berth allocation problem (BAP) or quay crane allocation problem (QCAP) [3]. These allocation goals are crucial in aspects of measuring the vessel's handling time. If operation causes a bottleneck phenomenon during the working, the productivity of the terminal handling equipment goes down, which ultimately degrades the total productivity in the container terminal. Thus, the container terminal needs to find the best efficiency and optimal process that outputs the best productivity in the container system. Among various container terminal handling equipment, the quay crane has been a critical component of the container terminal's productivity [4].

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Quay crane's operational plan is usually set before the ship arrives at the berth and decides how many cranes will be located based on the ship spec and the current berth status by the planner in advance. Planner's experiences help them to determine how to allocate quay cranes for vessels, and it can change depending on the situation. However, the container terminal always does not operate as it was planned. As evidence, approximately 30% of the changes were applied to the original scheduling plan data. The fact that the work changed in the existing scheduling means that about 30 percent can imply inefficiency in port operations. Since the original plan data does not have any considerations of exogenous factors, such as ship delay, unexpected equipment inspection, and employee shift, we aim to predict the quay crane's handling time by applying differentiated handling factors. By applying influential external factors from the quay crane, our approach outperforms by reducing error up to 54% compared to the conventional method, which measures unloading containers for one and a half minutes and loading containers for two and a half minutes. Our research's significant contribution is finding a new method to re-calculate the quay crane's working time besides the conventional method by utilizing the actual data.

The rest of this paper's discussion is organized as follows. Section 2 presents related work. Sections 3 and 4 discuss the proposed method and experimental results, respectively. Finally, Section 5 draws conclusions and looks ahead to future work.

2. **Related Work.** In port operation aspects, there are various operational sectors aimed at port operational efficiency with specific terminal facilities. Many studies focus on the quay crane as a critical performance indicator among container handling facilities in the terminal.

2.1. **Port operation efficiency.** There have been various researches going on with an idea of improvement of port operation. As mentioned before, increasing the port efficiency connects with increasing the total productivity of the terminal. A study on the *Development of Models Predicting Dwell Time of Import Containers in Port Container Terminals – An Artificial Neural Networks Application* [5] said the container is significant in all port terminals. All goods are loaded in containers, and all port equipment's core is the container. Thus, predicting the container's dwell time can help the port to decide on allocating containers in the yard. Furthermore, container dwell time can be gained insight by identifying the yard's properties in the container terminal. This paper suggested yard handling factors regarding containers to apply into an artificial neural network method.

With the increase of utilizing data in port, AIS data is also one of the critical factors. By collecting all AIS data, the port can predict the vessel's estimated time arrival [6]. Predicting the arrival time can affect the terminal operation efficiency since the port can easily decide berth allocation based on ETA (estimated time arrival). In addition, AIS data showed that ship destination forecasting plays a vital role in improving the efficiency of industry decisions and ensuring a safe and efficient marine transportation environment [7]. Further, utilizing AIS data, the vessel's delay can be detected to reduce operating equipment costs in the terminal [8]. These researches based on AIS data showed that the implications for improving the operational efficiency of terminals and ports using AIS data are growing.

2.2. **Quay crane working time.** The key performance indicator of the port operation system is known as quay crane. After the vessel arrives at the berth, containers expect the quay crane to conduct operations with the best efficiency [9]. This is the starting point where container flow starts in the container terminal. If the quay crane does not perform effectively, the quay crane becomes a bottleneck that the yard truck and the transfer crane's productivities can be reduced virtually. Since the port terminal targets the highest productivity (van per hour), quay crane's job is essential.

In a micro perspective, the cycle time of quay cranes in the container terminal was captured in the study about measuring the container handling cycle time of the advanced quay cranes that involve several handling components [10]. In this research, the advanced quay crane concept proposes a distinguishable approach from the previous research by considering the waiting time for a trolly as an uncertainty in the quay crane movement.

Another research on estimating vessel handling time proposed capturing the effect of terminal payout parameters and crane service time variabilities with quay crane's cooperation [4]. This paper obtained the actual quay crane's performance indicators based on the aspects of maintenance and repair. Jo and Kim [4] emphasize a management tool to guide future ship-to-shore container crane inspection, and the results provide useful insights into future container crane equipment operation improvements. In addition, Phan-Thi et al.'s [11] paper considers the quay crane's cycle time as the difference between the first lift time and the last lift time with the ranges between 2 to 5 quay crane per vessel from a container terminal in Rotterdam. Stepec et al. [12] proposed a method to predict the vessel's turnaround time by investigating the use of external environmental data such as weather data to enhance the accuracy of the available data and improve the performance of the developed system.

3. **Method.** In this section, the problem definition for quay crane working time and the proposed model for predicting using bootstrapping and the multi-layer perceptron method are defined. After defining the significant external variables which are influential to quay crane's productivity and the container terminal's productivity, these elements apply to two different methods: bootstrapping and multi-layer perceptron.

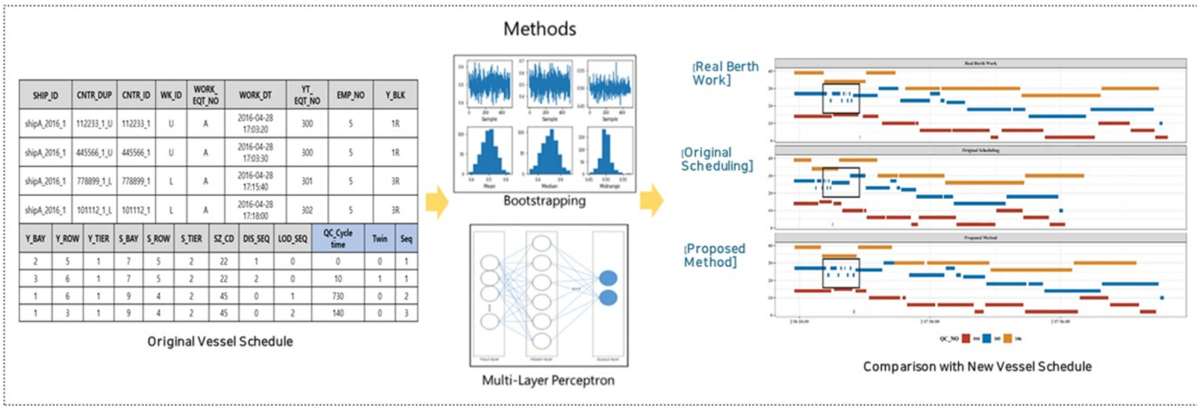

FIGURE 1. Methodology layout

3.1. **Problem definition.** The conventional quay crane operation time was measured in standard calculations, container unloading time is 1 minute and 30 seconds, and container loading time is 2 minutes and 30 seconds. In the advanced approach, other attributes applied to the handling time in the quay crane are the temporary availability at the vessel as ready time, initial positions, moving time, and time window. Although there are considerations of bay areas, container stacks, and more, these measures were considered an objective function as a maximum value or summed up for all tasks or cranes [3]. To overcome the simple calculations approach, we define various meaningful external variables of the quay crane. Variables are dealing with twin containers, changing working operation, employees shift, container types (Full, Empty, Danger, Bundle, Reefer), or the quay crane's movement along with the berth.

3.2. **Models.** We used vessel plan data from one of the ports in Busan. With external factors that we could get from the data, we applied these indicators into bootstrapping and the multi-layer perception, respectively.

4. **Experiments.** We first analyzed the conditional quay crane's cycle time based on the quay crane's properties under 410 vessel plan schedules. We preprocessed the data to define exogenous factors such as twin container, bay clusters, work type change, bay cluster change, container type (Full, Empty, Danger, Bundle, Reefer). Each indicator has different mean and median ranges, which leads us to establish our assumption of affecting the quay crane's handling time.

4.1. **Cycle time of quay crane.** Our data does not represent the exact starting time of quay crane, so we utilized the quay crane's unique equipment number with a working time to measure each cycle time by calculating the time difference under the same index of the vessel with the quay crane equipment number. Since working time is arranged by ship and quay crane number, we could generate the quay crane cycle time using Equation (1).

$$\text{QC\_Cycle\_time}_{(i)} = \text{QC\_Cycle\_time}_{(i)} - \text{QC\_Cycle\_time}_{(i-1)}, \text{ where } i \geq 2 \tag{1}$$

4.2. **Twin container generation.** Another data preprocessing was conducted for detecting twin containers. Since our method wants to measure the quay crane's working time accurately, we made a new column for measuring whether the quay crane operated with twin containers or not. As mentioned before, the traditional method of calculating quay crane's working time was based on the total container counts by working types (Unloading and Loading). This method does not consider quay crane's working factor dealing with twin containers.

From our Figure 2, we can see the same quay crane equipment number A has the same yard truck number Y1, and the QC_Cycle_time is 10 seconds. This emphasizes the quay crane's work operation of twin containers. If the yard truck receives twin containers from the same quay crane equipment under the same vessel, a yard truck delivers the two containers at once.

Vessel	Container	Work Type	Quay Crane	Work Time	Yard Truck	Employee Number
Ship_A	1	U	A	2016-04-28 17:03:20	Y1	5
Ship_A	2	U	A	17:03:30	Y1	5
Ship_A	3	L	A	17:10:00	Y2	5
Ship_A	4	L	A	17:20:50	Y3	5
Ship_A	5	L	A	17:25:28	Y4	5

BAY	ROW	TIER	Size	DIS_SEQ	LOD_SEQ	QC_Cycle time	Twin	Seq
5	5	2	20	1	0	0	0	1
7	5	2	20	2	0	10	1	1
7	4	2	40	0	1	390	0	2
9	4	2	40	0	2	650	0	3
11	5	3	40	0	3	278	0	4

FIGURE 2. Data-frame with cycle time and twin generation

4.3. **External factors from the quay crane.**

Bay clusters. One of our different approaches is defining bay clusters for each vessel. From Figure 2, there is a column named BAY. BAY column from Figure 2 represents the bay location where the container belongs to, and each vessel plan has its units of bays. The reason for clustering bays is to accurately measure the quay crane's moving job at each

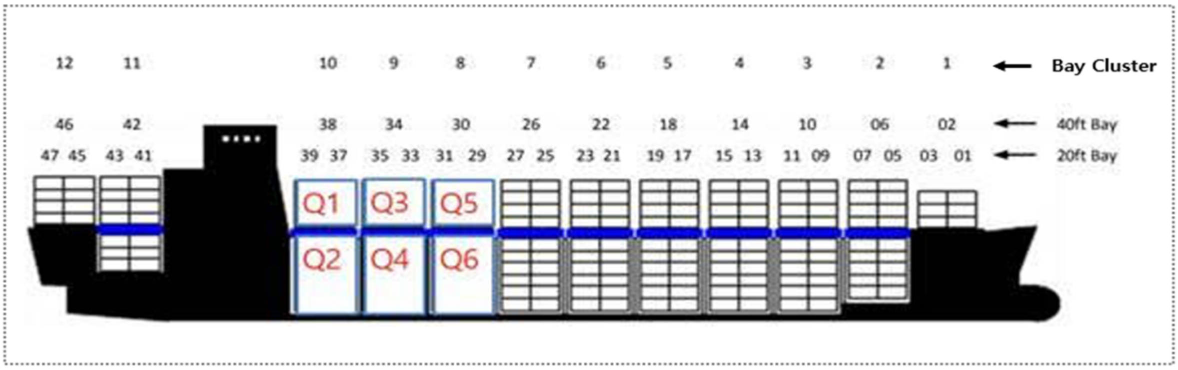

Figure 3. Bay clusters example

bay and measure the movements made by the quay crane. We consider the bay cluster's change can be one of the quay crane's operational aspects that affect the quay crane's actual cycle time.

The quay crane often moves along the nearest bay except when the quay crane should move to another vessel. Bay cluster helps us know the quay crane's movement time component as one of the quay crane handling factors. Table 1 below represents the external factors and examples of conditional distributions of a few elements used in our experiment.

Table 1. External factors with examples

Characteristics	**Conditions example**	**QC_Cycle_time (sec) example**	**Mean, median**
Container type (Danger, Bundle, Reefer)	Loading_Bay_Moving	[265, 269, 420, 356, 201, 108, 136, 144, 194, 267, 177, 504, 511, 443, 273, 107, 290, 495, 615, 585, 614, 402, ...]	[284, 231]
Bay cluster movement	Loading_Bay_not_Moving	[171, 129, 186, 133, 135, 293, 169, 133, 167, 240, 241, 389, 113, 115, 197, 198, 342, 113, ...]	[171, 130]
Work type change	Loading_WorkType_Change	[448, 747, 464, 609, 582, 340, 429, 97, 569, 371, 724, 625, 136, 693, 617, 682, 765, 646, 402, 770, 83, 740, 533, 135, ...]	[446, 530]
Employee shift	Unloading_Bay_Moving	[258, 115, 77, 102, 97, 115, 92, 73, 472, 122, 76, 792, 282, 429, 549, 83, 221, 345, 601, 638, 472, 518, 565, 205, 140, 353, ...]	[266, 208]
Single/Twin	Unloading_Bay_not_Moving	[166, 61, 114, 156, 58, 70, 98, 112, 106, 122, 128, 70, 545, 547, 100, 84, 104, 253, 127, 174, 105, 129, 129, 239, 123, 76, 392, 86, 88, ...]	[143, 105]
Full/Empty	Unloading_WorkType_Change	[505, 310, 387, 679, 374, 379, 421, 236, 240, 384, 291, 61, 718, 273, 668, 235, 723, 89, 104, 173, 356, 207, ...]	[357, 330]

As shown in Table 1, the mean and median for each factor have different ranges, emphasizing the quay crane's different cycle times depending on exogenous situations. After defining the factors, randomly select the cycle time from the conditional distributions to generate a new quay crane handling time, depending on the different circumstances. The first column in characteristics represents the specific factors we extracted from our data to apply to bootstrapping.

We verified the effect of the external variables on the processing time of the actual quay crane by error reduction in bootstrapping method compared to the traditional method. The newly calculated bootstrapping way by applying external variables is for establishing the assumption whether they are suitable for applying the multi-layer perceptron model later and confirmed them as new impacting external factors on the quay crane's working time.

4.4. **Results and discussion.** We apply the bootstrapping method to generating the new quay crane cycle time to build the whole working time and compare it with the original data-frame in Figure 2. The quay crane cycle time is randomly picked by different conditions when we generate a new cycle time. Figure 4 shows five random samples from the actual working plan with the new bootstrapping working time plan and the traditional working time plan. We learn that bootstrapping with external factors has significance in operating the quay crane, which ultimately reduced the error compared to the standard method.

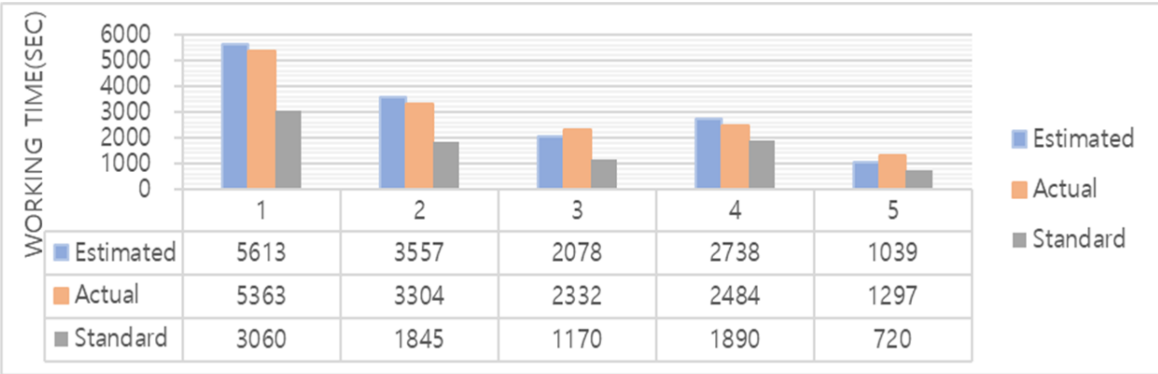

FIGURE 4. Comparison of conventional method and bootstrapping method

As a result of sampling the new time-window from conditional distributions, the bootstrapping approach reduced RMSE by approximately 36.9% from the traditional way of calculating the quay crane working time. In addition, by following the bootstrapping method, the total productivity of the quay crane has increased up to approximately 10% as well.

To further extend our approach, we apply multi-layer perception with the quay crane's handling factors. Table 2 shows unique elements of the quay crane that we processed in the bootstrapping method. We implement these factors from Table 2 in the multi-layer perceptron to calculate the quay crane cycle time more accurately. By setting unique characteristics with one-hot-encoding to put into multi-layer perceptron, the new way of calculating the quay crane was established.

TABLE 2. External handling factors of the quay crane data-frame

Work type	Full/ Empty	Container type	Bay cluster movement	Work type change	Employee shift	Twin or single	QC_Cycle_ time (sec)
U	F	Original	Bay_NonChange	WK_ID_NonChange	EMP_NonChange	Single	86
U	F	Original	Bay_NonChange	WK_ID_NonChange	EMP_NonChange	Twin	75
U	F	Original	Bay_NonChange	WK_ID_NonChange	EMP_NonChange	Single	124
...	...	...	...	...	...	...	...
L	F	Danger	Bay_NonChange	WK_ID_NonChange	EMP_Change	Twin	258
U	F	Bundle	Bay_Change	WK_ID_Change	EMP_NonChange	Single	252

We train our data from Table 2 in a multi-layer perceptron (MLP) model. Properties from the previously extracted conditional distributions were applied with one-hot encoding for inclusion in the MLP model. One-hot encoded inputs were learned through MLP models with the parameters in Table 2. Results derived through MLP reduced errors more than bootstrapping using conditional distribution.

Table 3. RMSE comparison of each method

	Conventional	Bootstrapping	Multi-layer perceptron
RMSE	1.46	0.92	0.67

As we go through the multi-layer perceptron model, the accuracy of predicting the quay crane increased that even better than the bootstrapping approach. Table 3 compares the RMSE of each output.

The bootstrapping approach reduced errors in actual handling time relative to conventional methods through external variables affecting the quay crane, and the MLP model showed significantly improved results when applied to deep learning by utilizing identified external variables.

5. **Conclusions and Future Work.** In port operation, the bottleneck phenomenon of terminal handling equipment has a significant effect on overall operational efficiency. In particular, about 30% of re-scheduling occurring in the quay crane shows that the total productivity of the container terminal is degraded. The working time of the quay crane, which was previously measured by the traditional method, does not include variables from the actual phenomenon, so it is very different from the actual operating time, which makes it difficult to accurately calculate the work queue of the quay crane. Our method of defining the external factors of the quay crane has improved in the accuracy of estimating the quay crane's handling time in terminal operation and has contributed to significantly reducing errors through the multi-layer perceptron. It is communicated that future advanced operational plans help to improve the container terminal's efficiency by applying potential external impact variables. In the future, we plan to employ external factors of the quay crane to measure the quay crane's handling time more accurately by advanced deep learning methodologies.

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