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# A System Based on Fuzzy Logic to Manage Operations in Container Yards

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**Abstract**— This article focuses on the assignment of arrived containers to pre-existing stacks stored in one of the container yards, particularly when the containers' date of departure and time are unknown. This becomes more difficult when different-sized, typed, and weighted containers needs be stored in pre-existing containers yard. The main objective is to create a Fuzzy Knowledge-Based System (FKB\_CYM) that considers practical factors and limitations such as container quantity per stack and customer, type, size, and weight. Various tools and methodologies are used, including Discrete Event (DE), Fuzzy Knowledge-Based Modelling (FKBM), and a Neighborhood Algorithm (NA). The paper thoroughly discusses and evaluates the system's findings.

**Keywords**—component; Fuzzy Logic Optimization, Container Yard Operations, Neighbourhood Heuristic Algorithm.

## I. INTRODUCTION

Container terminal plays a crucial role in the management of supply chains by serving as inter-modal interfaces, and competition is driving the need for more efficient freight handling. With the increasing necessity to handle containers, improving container terminal operations is a priority (Ries et al., 2014). The container-yard side of rail container terminals is the most important area for containers' storage and retrieval operations but managing yard operations for efficient and easy retrieval of containers is complex, especially when the departure time is unknown or unexpected (Chen and Lu, 2012). Challenges such as allocation of storage space, assignment of container's location, and other constraints related to container storage add to the complexity (Zhen et al., 2013). This study aims to address these challenges by creating a fuzzy knowledge-based system that solves real-life storage and retrieval problems, even with pre-existing containers. The paper presents a methodology to achieve this.

When developing a container yard operations system, practical real-life factors and constraints are taken into consideration to improve its effectiveness. The system mainly focuses on the number of containers in each stack and the similarity of

containers in each stack. Constraints include weight, size, and type. Stacks are allocated based on the aforementioned factors and constraints. The paper's organization is as follows: Section

## II. LITERATURE REVIEW

Different fuzzy logic models have been developed to address various aspects of container yard operations. One of the models aimed to reduce the ration of containers relocation with unknown times of departure by considering stack height and the same sizes, types, and weights of containers (Zehendner et al., 2017). Another model used fuzzy optimization to minimize unbalanced workloads and the number of blocks for the same group of containers but did not consider stack utilization (Liu et al., 2010; Jin et al., 2004). An intelligent simulation model was also proposed to reduce total operation time, but it did not group containers based on their customers with different sizes, types, and weights. The fuzzy DEMATEL method was used to identify factors that affect the interests of container terminals, including centrality, quality of service, and efficiency. Lastly, a study compared stacking strategies of "ordered" and "random" for proper slot assignment, assuming containers of the same size and type but with different weights (Khajeh and Shahbandarzadeh, 2022; Lawrence and Chwan-Kai, 2001).

Janith et al. (2021) studied the real time yard planning decisions impact using a model with rule-based system to identify precise yard locations for containers arriving. At the yard in (Huynh, 2008), non-mixed and mixed methods were proposed to solve the container storage operation problem and evaluate the effect of storage policies on various criteria. However, all containers had the same size, type, and weight. Mathematical functions were used in (De Castilho and Daganzo, 1993) to analyze strategies of segregation and non-segregation for the container storage problem to reduce handling effort, but without considering grouping containers based on customers or different sizes, types, and weights of containers. (K. Kim, and H. Kim, 1999) developed mathematical difference equations to improve the proposed strategy of segregation proposed in (De Castilho and Daganzo, 1993) by considering static, periodic, and continuous changing

arrival patterns for containers, but the stored containers in bays was a modeling factor.

The article (Kim, 1997) used mathematical equations to solve the container stacking problem by estimating the number of re-handles required for the best pick up practice of containers in a bay. However, the utilization of stacks with different weights, sizes, and types of containers was not taken into account. In (Woo and Kim, 2011), a mathematical model was proposed to allocate storage space to different groups of containers, including those of different sizes, port destinations, and stack heights, with the goal of minimizing the reservations number for group of each container. However, the model did not consider different weights and types of containers. Finally, (Zhang et al., 2003) introduced a rolling horizon approach to minimize workload in storage yard blocks and transportation distance between the blocks storage and berths of vessel, but the allocation process did not consider stack utilization and different weights, sizes, and types of containers.

In (Yang et al., 2015), an Integer Programming Model was developed to solve the Problem of Stacking Position Determination (PSDP) for containers. The model increased the circulation of containers and reduced any unbalances in workloads and crane movement, but it did not consider height of stack or different weights, sizes, and types of containers. Similarly, (Ayachi et al., 2010), developed Genetic Algorithm to allocate storage space for containers to meet customer delivery deadlines and reduce re-handles, but did not consider grouping containers based on customers or containers of different sizes. Another Genetic Algorithm model (Ayachi et al., 2012) was developed to allocate optimal storage space for import and export containers and minimize re-handling operations, but did not consider factors such as stack height or container sizes and weights. Finally, in (Junqueira et al., 2016), a Simulation-based Genetic Algorithm was developed to minimize unproductive container movements but without considering stack height or container sizes.

The authors of (Park et al., 2011) proposed a new algorithm based on online search to reduce times of both re handling and retrieval in container stacking operations. The algorithm grouped containers based on destination, size, or weight, but did not consider stack utilization or container type. In (Ozcan and Eliyi, 2017), introduced an algorithm based on rewards to minimize container re-handling and crane travel time in the yard, taking into account container size, weight, and type, but not grouping containers based on customers. Additionally, (Zadeh, 1975) did not address grouping containers based on customers for solving the outbound container stacking problem. Although several factors were considered in previous studies, such as stack height, container grouping by customer, size, type, and weight, further research is needed to explore additional storage constraints such as the number of containers per stack, similarity between containers in a stack, and other factors for a more comprehensive solution to the container storage problem.

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### III. RESEARCH PROBLEM

Effectively managing the operations of container yards is a challenging task attributed to several restrictions, such as container weight, size, type, and quantity, as well as uncertainty around the departure schedule. The container yard layout in Figure 1 illustrates pre-existing containers, which are managed using reach stackers during storage, retrieval, and re-handling. However, a challenge arises when new containers arrive with different characteristics than the pre-existing containers, and the departure schedule is unknown. Third-Party Logistics (3PL) companies collect containers using their trucks and dispatch them to the terminal without prior notice, making the storage operation even more complicated. The following section will outline the strategies and tools used to create a container yard management system.

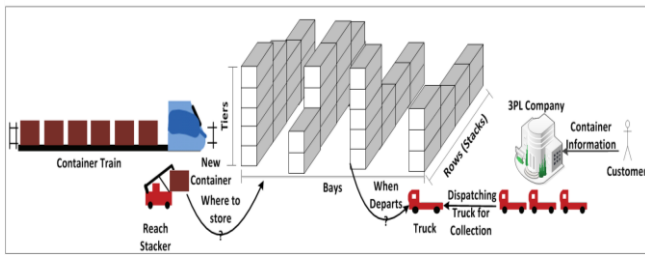


Figure 1. Container yard layout

#### IV. METHODOLOGY

A. The creation of 'FKB\_CYM', a fuzzy knowledge-based system used to manage yards

To tackle the issue of containers allocation stacks without knowledge of their time of departure, a Fuzzy Knowledge-Based approach is utilized. Since the exact time of arrived trucks to collect containers is uncertain, this approach is deemed necessary. To simulate the process of re-handling containers, the "Neighborhood" Heuristic Algorithm is applied. Additionally, the DE method is utilized to model the various stages of container arrival, storage, and retrieval. The structure of the "FKB\_CYM" system is outlined in the following section.

B. The 'FKB\_CYM' system's structure

This section describes the design of a new Fuzzy Knowledge-Based (FKB) model, which consists of three main components: input, process, and output. Figure 2 illustrates the structure of the system. The input component includes details and specifications about the container yard, while the process component uses a combination of methods to handle the inputs. The output component provides Key Performance Indicators, sorted by time of operation, criteria of yards, truck and utilization of resources. The specification information includes input parameters like the container yard definition, customer and company numbers, truck travel time, and container train inter-arrival time. The container yard information comprises container size, type, weight, and the number of containers per stack, taking into account the containers' similarity belonging to the same customer. The process component includes three modules of Heuristics Algorithm, FKB, and DES.

The Fuzzy Knowledge-Based system is initiated by inputting information related to the yard into the FKB module, and information of specifications into the allocation of storage and all other modules of collection operation. The storage allocation operation uses the specification information to initiate the yard's container storage, while the number of trucks for container delivery is input into the operation of collection. Based on the information of inputs, the FKB module assigns a stack for container storage by calculating level of acceptability per stack and selecting the highest level one. The container is then stored in the designated stack, and the yard information is updated accordingly. When a container needs to be retrieved or collected, it is taken and loaded onto a truck, and the heuristics algorithm is used to re handle any

containers above the required one. After the collection phase is complete, updates need to be conducted to the container yard information.

The DE approach is used to mimic both the trains' and vehicles' arrival and departure, as well as storage and retrieval operations. The output module provides metrics such as processing time, space utilization, truck utilization, and resource utilization. Processing time involves times of storage and retrieval of containers, and the related waiting times, while utilization of space includes the designated yard, bays, and stacks utilization. Resource utilization includes reach-stacker usage and container re-handling frequency, while truck utilization includes the number of trucks used, unused, and the containers transported per truck.

In the upcoming section, each technique used in creating the 'FKB\_CYM' system will be elaborated upon.

a) Fuzzy Knowledge-Based Approach (FKBA) for Storage Operation

This section will offer a comprehensive description of the different phases that constitute the Fuzzy Knowledge-Based method. These stages include the fuzzi-fication stage, fuzzy rule execution, and the de fuzzification phase. The outcome of this process is an output parameter known as the acceptability level of storage ( $\alpha$ ), which gauges the stack value in the decision-making process.  $\alpha$  value is produced for each stack in the container yard ( $i$ ) based on the input variables and restrictions discussed below. The location for storing an incoming container is determined by the stack with the highest  $\alpha$  value. Two factor's types are investigated in this module.

- Factor 1: Containers' Numbers per Stack

The initial input parameter in this module is denoted as  $N$ , representing the containers number stored in stack  $i$ , which is referred to as  $N_i$ . An increased containers numbers per stack will decrease the level of acceptability ( $\alpha_i$ ) for the incoming containers. This is because a higher containers volume in a stack may lead to longer service times and an increased the re handlings amount, especially if the truck's arrival time is unknown. Thus,  $N_i$  is used to consider the containers number in each stack.

- Factor 2: Containers per Stack Similarity

The second input parameter ( $S$ ) of the module is used to assess how similar the arriving container is to those already in stack  $i$  ( $S_i$ ). If the containers in the stack are similar to the incoming container, it results in a higher level of acceptability ( $\alpha_i$ ) for the arriving container. The module evaluates similarity by considering the customer to whom the containers belong. Additionally, three constraints ( $W$ ,  $F$ , and  $Y$ ) are used to evaluate weights, sizes, and types of container differences of the incoming container compared to the container in the topmost location of stack  $i$ . The weights, sizes, and types of the containers are determined and subtracted from the incoming container to evaluate these constraints. The module performs three stages of operations to determine a suitable container storage level, which will be explained in detail.

- The Stage of Fuzzification

In the fuzzification stage, the inputs and outputs of the

system are made fuzzy by assigning each variable a function of membership including linguistics definitions. The membership functions used in this approach have a triangular shape, and all variables are assigned to six linguistic variables, namely 'Very Low', 'Low', 'Medium Low', 'Medium', 'Medium High', and 'High'. For instance, the resulted variable,  $\alpha_i$ , has a triangular membership function with six linguistic variables. Similarly, the input variable,  $N_i$ , has three functions based on triangular memberships assigned to 'Very Low', 'Low', and 'Medium Low'. The membership function for  $N_i$  is illustrated in Figure 4. The second input variable,  $S_i$ , has a membership of triangular shaped functions similar to  $N_i$ , and its membership function is presented in Figure 5, where it is assigned to three linguistic variables or levels, namely 'Low', 'Medium', and 'High'.

Figure 2. The FKB Framework

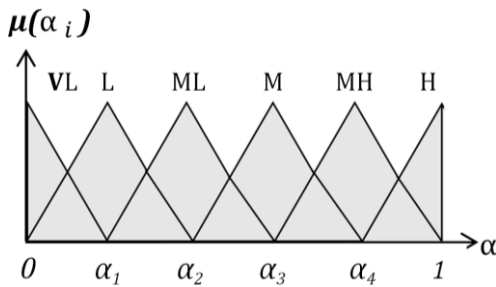


Fig. 3: Membership function for the output ( $\alpha$ ) using fuzzy logic

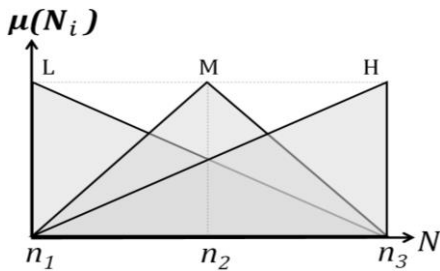


Fig. 4: The input ( $N$ ) using fuzzy logic membership function

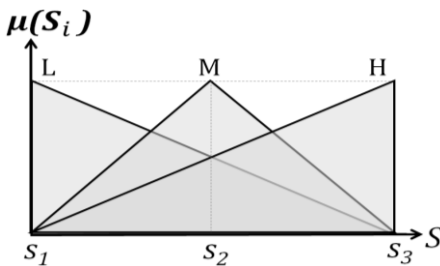


Fig.5: The membership function for the input ( $S$ ) using fuzzy logic

There is a set of three constraints, namely weight ( $w_i$ ), size ( $F_i$ ), and type ( $Y_i$ ), which share a single "Accept" set and are defined by precise membership functions. Figures 6, 7, and 8 depict the membership functions for  $w_i$ ,  $F_i$ , and  $Y_i$ , respectively, and they are identical for all three constraints.

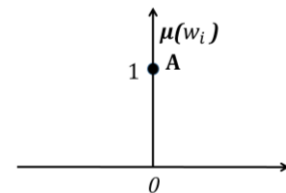
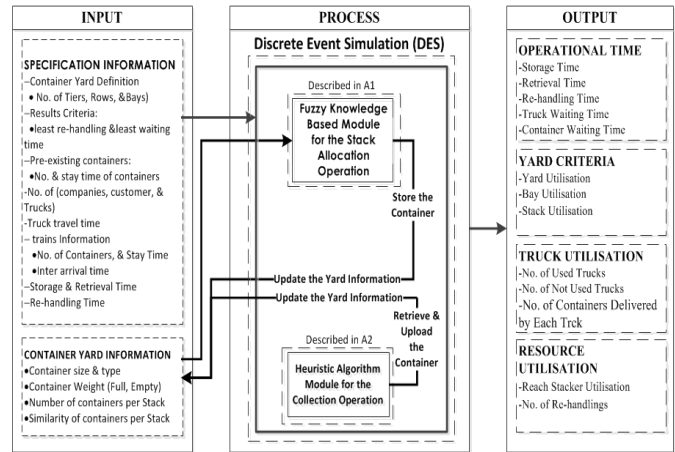


Fig. 6: The weight membership function

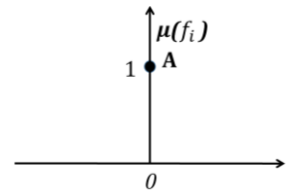


Fig.7: The size membership function

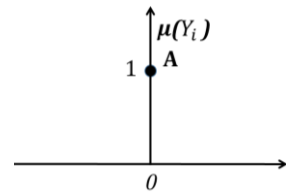


Fig. 8: The container type membership function

• The Fuzzy Inference Stage

To establish the relationship between the inputs and outputs variables, a set of fuzzy rules is formulated. These rules specify the impact of variable ( $N_i$  and  $S_i$ ) on the output variable and are developed based on an examination of the chosen input variables and their interactions (Zadeh, 1979). The rules are in "If-Then" format and are created using expert opinions, literature, observation, and logic. The objective is to minimize the amount of re-handling needed for the retrieval operation by considering the available location for an incoming container. Table I lists all the fuzzy rules created. A process of aggregation is utilized that involves manipulating the fuzzy information within the predefined rules. Once these rules are established, the minimum operator is used for aggregation (Zadeh, 1965). Equation (1) is then presented as the proposed approach for allocating containers in a stack. Finally, a value of truncation  $T_j$  is calculated for each rule  $j$ .

$$T_j = \min \left\{ \begin{array}{l} \mu_{(\bar{N})} n_i, \mu_{(\bar{S})} s_i, \mu_{(\bar{T})} t_i, \mu_{(\bar{W})} w_i, \\ \mu_{(\bar{F})} f_i, \mu_{(\bar{Y})} y_i \end{array} \right\} \quad (1)$$

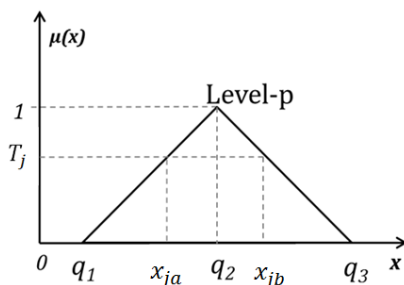
Earlier, the unique circumstance of  $w_i$ ,  $F_i$ , and  $Y_i$  is explained. Because the minimum is achieved in terms of operator, if the membership degree of a particular values for  $w_i$ ,  $F_i$ , and  $Y_i$  is calculated to equal 0 in any rule, the ultimate output for all values of  $T_j$  will equal 0 as well.

TABLE I. THE DEFINED FUZZY RULES

Rule #	$N_i$	$S_i$	$\alpha_i$
1	L(Low)	L(Low)	M(Medium)
2	L(Low)	M(Medium)	MH(Medium High)
3	L(Low)	H(High)	H(High)
4	M(Medium)	L(Low)	ML (Medium Low)
5	M(Medium)	M(Medium)	M(Medium)
6	M(Medium)	H(High)	MH(Medium High)
7	H(High)	L(Low)	VL(Very Low)
8	H(High)	M(Medium)	L(Low)
9	H(High)	H(High)	M(Medium)

• The De-fuzzification Stage

The de-fuzzification phase involves transforming an output fuzzified set into a clear, precise outcome. Several techniques are utilized for defuzzification, considering mean of maximum, center average, and center of gravity. For this particular investigation, the approach of centroid, which is an oriented implementation of a well-known center of gravity technique, is selected since it is the most frequently utilized and intuitively appealing method in most applications (Zimmermann, 1991; Zimmermann, 2001). To compute the center value for each rule ( $y_j$ ), the value of truncation  $T_j$  is computed from the resulted fuzzy sets  $\tilde{\alpha}$ . The entire gravity center is subsequently calculated by determining the related center values for each rule  $j$  ( $y_j$ ). Finally, the value of crisp output ( $y^*$ ) is determined utilizing the center of method of gravity, as illustrated in equation (6), based on the center values of each rule (Castro, 1995; Lee, 1990; Morim et al., 2017).



$$y_j = \frac{x_{ja} + x_{jb}}{2}, \text{ where;} \quad (2)$$

$$T_j = \frac{x_{ja} - q_1}{q_2 - q_1} = \frac{q_3 - x_{jb}}{q_3 - q_2}, \text{ where;} \quad (3)$$

$$x_{ja} = q_1 + T_j(q_2 - q_1) \text{ and } x_{jb} = q_3 - T_j(q_3 - q_2) \quad (4)$$

$$\therefore y_j = \frac{x_{ja} + x_{jb}}{2} = \frac{q_1 + q_3 + T_j(2q_2 - q_1 - q_3)}{2} \quad (5)$$

$$y^* = \frac{\sum_{j=1}^l y_j T_j}{\sum_{j=1}^l T_j} \quad (6)$$

a) The Neighborhood Algorithm for Container Re-handling

In order to get a container from a stack, it needs to be on the top. If there are other containers on top, they must be relocated to a different stack to make room for retrieval. A technique introduced by a previous study (referenced as (Ji et al., 2015)) is used in this research to handle container retrieval, called the "Neighborhood" Algorithm. This algorithm investigated a nearby stack that has an open slot, and checks if the top container in that stack matches the container's being retrieved in terms of its size and type. By doing so, the algorithm reduces the time it takes to retrieve containers by finding the closest stack that meets the constraints of the container. The algorithm starts by looking for an available slot in the nearest stack to the original one. If it is an empty stack, the container is moved there. If not, the algorithm checks if the container matches the size, type, and weight of the top-most container in the stack. If it does, the container is moved to that stack; otherwise, the algorithms look for the next stack. If all stacks are occupied, the container must wait for the next available slot. The algorithm can be summarized as follows:

1. Look for a free slot in the nearest stack to the original one.
2. If the nearest stack is unoccupied, go to 3; otherwise, proceed to 4.
3. Move the container to the nearest stack and then end the retrieval operation.
4. If the nearest stack is full, go to 5; otherwise, proceed to 6.
5. If all stacks are full, go back to 1.
6. Compare the to be moved containers' size, type, and weight with the top-most container in the nearest stack.
  - 6.1. If the container to be moved has similar size as the top-most container, go to 6.2; otherwise, go back to 1.
  - 6.2. If the container to be moved has similar type as the top-most container, move the container to the nearest stack and end the retrieval operation; otherwise, go back to 1.
  - 6.3. If the container to be moved has similar weight or less than the top-most container, move the

*container to the nearest stack and end the retrieval operation; otherwise, go back to 1.*

## II. CASE STUDY

The objective of the research was to evaluate a recently created management system for container yards, in partnership with Maritime Transport, a prominent container transport business in the United Kingdom. Maritime provides multimodal transportation solutions and is a crucial component of its clients' supply chain. The majority of the data inputs for the system were obtained from Maritime, which furnished details regarding the yard's layout, including rows, bays, and tiers, as well as the time between trains arriving, specifications of containers like size, type, weight, and customer and company information, as well as the number of trucks available for each company.

To assess the performance of the system of container yard management in handling a substantial quantity of current containers, a variety of inputs were required for the test. The test was modeled on a bustling yard that initially contained around 900-1012 preexisting containers that were stored for 2-4 days. The system utilized various resources, such as a container yard, container trains, trucks, and reach stackers. The yard was equipped with 45 bays, each of which had 5 rows that could accommodate up to 5 containers. There were 1-2 trains arriving per day, carrying 30-60 containers with varying weights, sizes, and types. These containers were transported to and from customers by five Third Party Logistic (3PL) companies, with each of which having 20-30 truck serving 7 customers. Each container has several recorded characteristics, such as its empty or full weight, small, medium, or large size, and type (indicated by a combination of size and number). The sizes were split into 5 small, 5 mediums, and 5 large categories, with LT3 being an example of a large container of type 3. The findings of the busy-yard scenario are discussed in the following section.

## III. RESULTS ANALYSIS AND DISCUSSION

This section discusses the results of the busy yard scenario utilizing the input values previously mentioned. The efficiency of the system is assessed by measuring the average utilization of the yard, amount of container re-handlings, the time taken for retrieval and re-handling, and the waiting time for trucks. Figures 10 and 11 depict the average utilization rates of rows and tiers, respectively. The findings reveal that row 1 has the highest utilization rate, as shown in Figure 10. Additionally, Figures 10 and 11 demonstrate that the number of containers in row 1 is greater than in row 5, which leads to a lower utilization rate in row 5. The highest utilization rate was found in tier 1, whereas the lowest was in tier 5. According to Figure 11, tier 1 has the highest average utilization rate at 78.12%,

while tier 5 has the lowest at 30.61%. The containers were initially stored in tier 1 before being moved to tiers 2 through 5. Consequently, the number of stored containers in tier one is higher than the ones stored in tier five. Fig. 12 depicts the total containers' number and the re-handlings number per row.

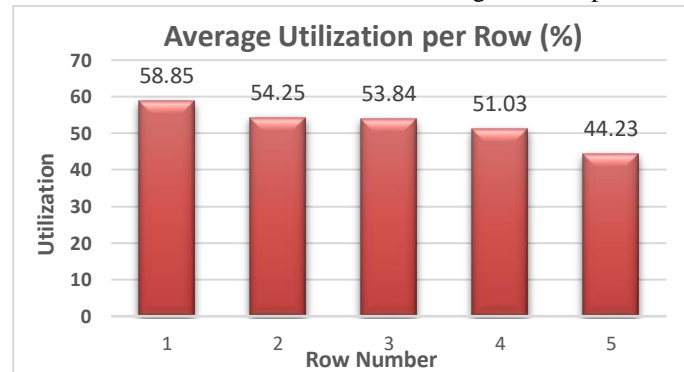


Figure 10. The average utilization of rows

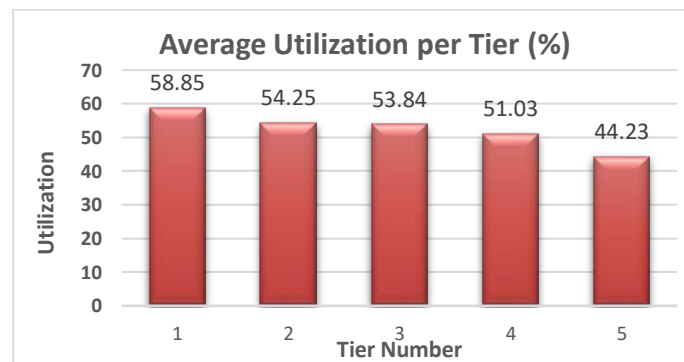


Figure 11. The average utilization of tiers

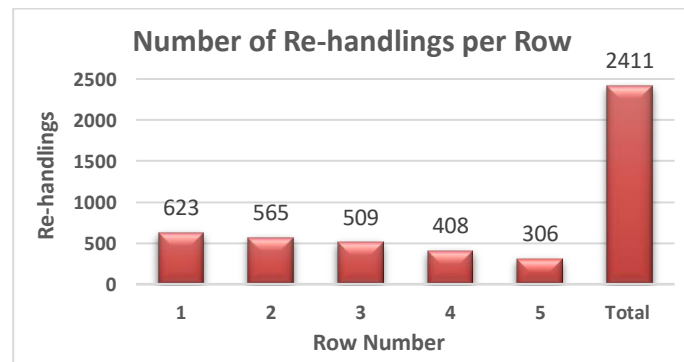


Figure 12. The re-handlings number per row

The findings presented in this section evaluate the performance of the container yard management system by measuring its average utilization, container re-handlings, retrieval and re-handling time, and truck waiting time using the input values mentioned earlier. Figures 10 and 11 illustrate the average utilization of rows and tiers respectively. Row 1 has the highest utilization, and row 5 has the lowest, indicating that storing more containers in a row leads to more re-handlings during the retrieval process. Figure 12 showed tall containers stored in the yard and all re-handlings per row.

Row 1 has the highest re-handlings, and row 5 has the lowest. Figure 13 shows the re-handlings amount per bay.

Bay 43 had the most re-handlings with 77, while Bay 45 had the least with 35, as shown in Figure 13. The reason for this is that there were a high number of stored containers in Bay 43 and a low number in Bay 45. All containers in the yard were recovered after an unexpected departure, which followed a triangular distribution. The total time it took to retrieve all the containers was 104.53 hours, with an average time of 0.06 hours per container. Each container was then loaded onto a truck and delivered to customers, with an average waiting time per truck of 1.9 hours. In cases where a container was buried underneath other containers, the top stored containers needed to be moved to other stacks in order to retrieve it, resulting in a total re-handling time of 74.6 hours during the retrieval process.

#### IV. CONCLUSIONS AND FUTURE WORK

A FKB system was created to tackle the allocating space problem for arrived containers alongside existing ones in the yard. The system employs a Neighborhood Algorithm to re-handle containers during retrieval and takes into account several factors and limitations, including the unpredictability of container departure dates and times. The system has been shown to be effective in efficiently storing and retrieving containers. The study revealed that rows, tiers, and bays with more containers during storage had more re-handlings during retrieval. The system will be improved by including the containers stored duration in the yard, which will be a focus of future work in this area aimed at enhancing container storage operations.

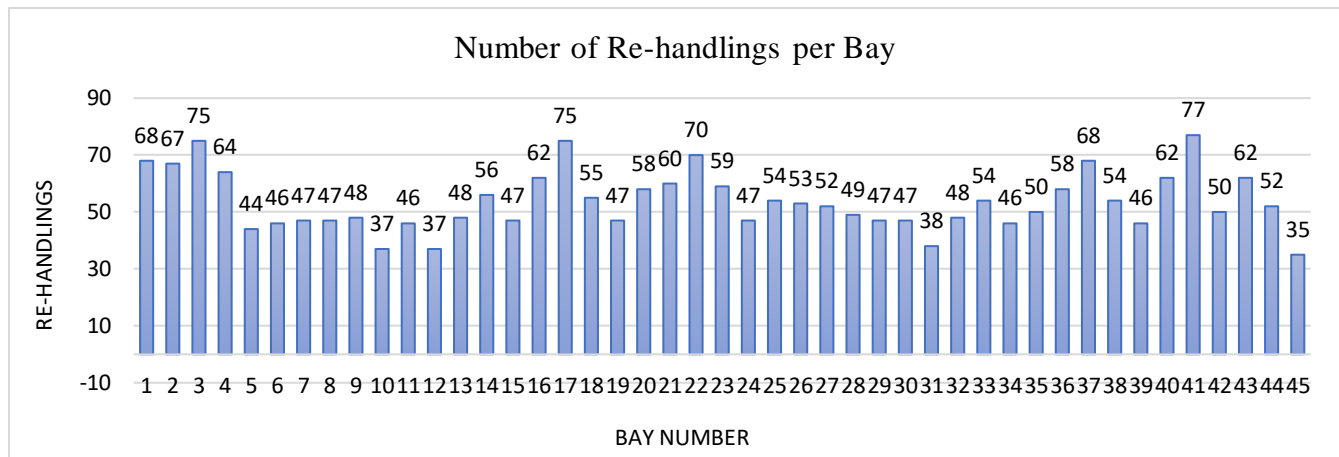


Figure 13. The re-handling amount per bay

#### ACKNOWLEDGMENT

We would like to thank Steve Parry, the business development manager at Maritime Transport, for his valuable support in providing all the required information.

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