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Optimization of Empty Container Operations by Demand Prediction and Simulation (Case Study: Shahid Rajaee Port)

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ABSTRACT

With the increasing trend of containerization in large ports, empty container provision and management have become a major logistics service at ports. Every day, a large number of empty containers should be available to be sent to different logistics yards for stuffing and export purposes. The empty container demand forecast can highly improve the time and resource management by both terminal operators and port authorities. In this paper, Shahid Rajaee Port, as the largest and most important commercial port in Iran is investigated. A private terminal operator is the main provider and responsible party for the majority of empty container operations. The optimization process of empty container operations using machine learning and artificial intelligence methods is investigated in this paper. Given the possibility of predicting the demand for empty containers, it is possible to reduce the daily operation volume through advanced planning and consider necessary measures regarding the appropriate spatial distribution of empty containers before the demand arises. A simulation software is also used for different managerial scenarios. The results show that by sending half of the monthly predicted demand of only six out of 75 depot yards as well as the container yard in off-peak times, the total empty container delivery time can decrease up to 30 %. Besides that, planning a schedule for an asynchronous call of trucks to pick up the requested empty containers has proved to reduce the queue lengths and average waiting times up to 90%.

1. Introduction

In Shahid Rajaee port, empty containers are provided to shipping companies in off-deck depot yards as well as container vessels waiting to load empty containers at berths. The management of distribution and delivery of empty containers is carried out after the demand is determined. The process is important because any disruption can cause delays in delivering empty containers resulting in customers’ dissatisfaction and even negative impact on the country's export process. An exclusive yard for the storage of empty containers (ECT), is located in the western part of Shahid Rajaee port on a land area of 11.5 hectares, with a static capacity of approximately 17,000 TEU of empty containers based on the layout model and operational constraints. Currently, it is mainly used for storage of 20-foot containers. 40-foot containers, which account for less than 10% of the empty container operations, are stored in another yard in case of emergency situations or insufficient storage space.

Due to the high demand from numerous customers, the management of distribution and delivery/receipt of empty containers is accompanied by many complexities, which, during peak demand, result in queuing and reduced operational efficiency at the port. This issue becomes even more complicated during times when the demand for exporting empty containers by vessels exists since the volume of demand from vessels at the quay is very high and must be dealt with within a limited number of days to avoid financial penalties such as demurrage or shortage of containers. Therefore, identifying the demand cycle in empty containers management and decision-making process can lead to improving the performance of this cycle during peak demand and daily operational activities.

2. Related Works

Research in the field of artificial intelligence in container operations management include different issues such as transportation planning and scheduling, optimizing transportation capacity at ports, predicting future demands, resources management, etc. In most studies conducted, artificial intelligence and machine learning have been utilized to provide optimization algorithms for operational management processes. By analyzing historical data related to the transportation of empty containers, machine learning algorithms can identify patterns and predict future needs based on them. This prediction can assist ports in optimizing resource allocation and transportation capacity, thus preventing the need for excess empty containers or addressing their shortage. According to the conducted surveys, many prominent companies in the shipping industry, including Maersk, MSC, and CMA-CMG, as well as companies involved in port operations and logistics chains such as DPworld, directly and indirectly utilize artificial intelligence (AI) in their maritime and port services.

As an example, Nile Dutch Africa Line BV (NileDutch), a large shipping company specializing in container and break-bulk shipping between West Africa and the rest of the world, has utilized AI, machine learning and intelligent algorithms for empty container handling and relocation in collaboration with Transmetrics, a leading provider of predictive optimization and AI tools for logistics. The two partners jointly developed a predictive asset management software to streamline empty container flows which provides daily rolling AI-driven forecasts for the next 10-12 weeks based on the historical data and the external factors influencing the demand. The system also suggests the most optimal and actionable plan for empty repositioning, storage, repair & maintenance for the next 12 weeks, which takes into account all the related costs (including grading, stevedoring, gate costs, etc.). [1]

In 2019, Liu Yuan investigated the effect of machine learning in predicting empty container volumes, using five machine algorithms on the Los Angeles Port and Long Beach Port datasets. The best machine learning algorithms for predicting the volume of empty containers are introduced and compared with existing empirical methods and mathematical statistics methods. He has concluded that machine learning needs to combine multiple models or select more high-correlation feature quantities to improve performance on such prediction problems. [2]

In 2020, Shankar et al. used long short-term memory (LSTM) networks to forecast container throughput of the Port of Singapore. The LSTM model performance was compared with seven different time-series forecasting methods, including autoregressive integrated moving average (ARIMA). The results showed that LSTM outperformed all other benchmark methods. [3]

In 2022, a number of multivariate predictive models based on deep learning were developed to forecast container throughput in the port of Barcelona. The models' performances were assessed to identify the best model architecture and set of hyper parameters. A comparative analysis of the out-of-sample accuracy of some models in predicting the container traffic volume was carried out. [4]

In 2022, two novel approaches based on machine learning and probabilistic techniques were introduced to predict the future weekly availability of empty containers for more than 280 locations worldwide. A data set of more than 100 million events with different stages of container transportation process were used. Both models were based on a two-step forecast logic in which the expected location of a container was first predicted and the timestamp for arriving at that location was estimated afterwards. Artificial neural networks and mixture density networks were used in the machine learning model for the containers' movement forecast. The comparative assessment of the model results versus the actual availability of containers indicated the outperformance of the neural network approach over other approaches concerning every evaluation metric. [5]

Seaport resilience analysis and throughput forecast has been conducted for Busan port in 2022, using a deep learning approach. The mentioned research deals with data analytics for analyzing port resilience and a new paradigm for productivity forecasting that utilizes a hybrid deep learning method. Nonlinear analytical methods have shown that throughput demand at Busan port has a complex behavior due to business fluctuations and uncertainties. A combination of long short-term memory (LSTM) and random forest (RF) approaches have been utilized for port throughput forecasting. The LSTM networks have shown high effectiveness in time-series forecasting tasks and RF is proposed as a complementary method to mitigate residual errors from the LSTM scheme. [6]

The literature review has shown that system simulation tools can be very effective in operational optimization of ports and terminals. Container terminal simulation offers several advantages including performance evaluation, resource allocation optimization, reducing equipment idle times, minimizing vessels and trucks waiting times and improving overall operational efficiency. As an example, in 2015, a simulation of the internal transport system of empty container terminals was conducted using SIMIO software at Delft University of technology. The objective of the study was to determine the most suitable transport system for internal traffic within the terminals. [7]

In 2016, the optimal layout for a container terminal in Sri Lanka was selected using simulation. Considering that container movements within the terminal incur costs and time, choosing an appropriate layout for the containers can lead to cost and time reduction in terminal operations [8].

Another study regarding the optimization of empty container operations is the simulation of the empty container transfer process between the quay and the terminal at the Tanger Med port in Morocco, which was carried out in 2017. In this study, the design of transfer operations and the simulation of empty containers, considering related activities at the container terminal, were proposed. The simulation was performed using ARENA software for a one-week time frame. The main idea of the modeling was to propose methods for allocating empty containers to storage locations based on vessel destination, movement time, and container type [9].

In 2018, another study was conducted to simulate and analyze container movements using ARENA software. In this study, the terminal's cranes, quay, internal transportation vehicles, and operators were examined. The results of this research provided a new simulation model for a developed terminal dataset, in which the terminal's utilization, waiting time, and resource counts were determined [10].

Another study on optimizing operations at container terminals was the analysis of container dwell time at the Surabaya terminal in the Tanjung Perk port in Indonesia in 2020. This study utilized ARENA software for discrete event simulation to model the terminal's operations and employed the RCA (Root Cause Analysis) method to analyze pre-simulation data. The resulting simulation model was an interpretation of a real system that combined logic and mathematics [11].

Prediction of empty container demands using LSTM method has been conducted for Shahid Rajaee port in 2024 in which the total demand of 72 terminals has been predicted for one month based on 22 months' available data. The predicted result for the representative month demand has shown only 0.3 percent deviation from the real demand value [12], [13].

3. Material and Method

In this section, the available dataset and the methodology for data interpretations are described.

3.1. Available Data Set

In the present paper, AI-based methods have been used to improve the spatial and temporal management of empty container allocation to the off-deck depot yards in Shahid Rajaee Port. The monthly demand of the empty container is predicted based on the demand history which is available on a daily basis for 25 months from August 15, 2021 to September 22, 2023 [14]. The data set includes the number, type, size, loading date, transportation agent, and destination depot yards of empty containers. Based on the initial analysis of the available data during the mentioned time period, out of approximately 245000 allocated empty containers, 93% were 20-foot and 7% were 40-foot. Therefore, the majority of the empty container movements between depot yards are related to the transfer of 20-foot containers. Consequently, the present study focuses on the operations of empty 20-foot containers. The daily and monthly 20-foot empty container allocations to off-deck depot yards and deck container yard (CY) is shown in Figure 1 and Figure 2 respectively. As shown in the Figures, the demands from vessels at CY are occasional but large which led to high total demands for empty containers at the empty container Terminal (ECT) at certain times. Empty containers are sent to various off-deck depots at Shahid Rajaee Port. The monthly average demands of 75 off-deck depots (named T1 to T75) and CY are shown in **Error! Reference source not found.** which indicate that the majority of demands are dedicated to a limited number of depots, and the demands of others are relatively low.

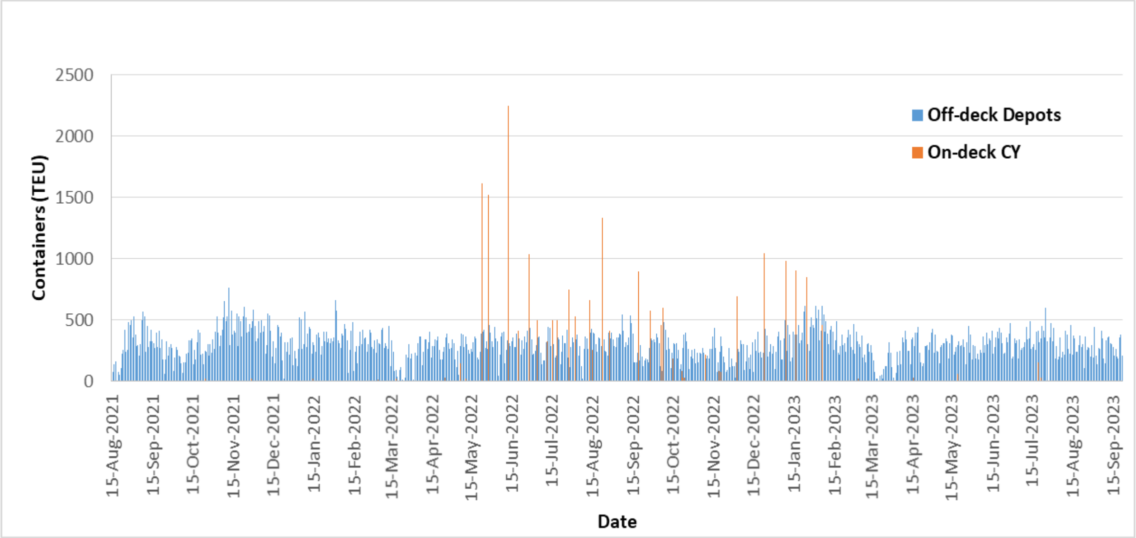

Figure 1. Daily 20' empty container allocations to off-deck depots and on-deck container yard (CY)

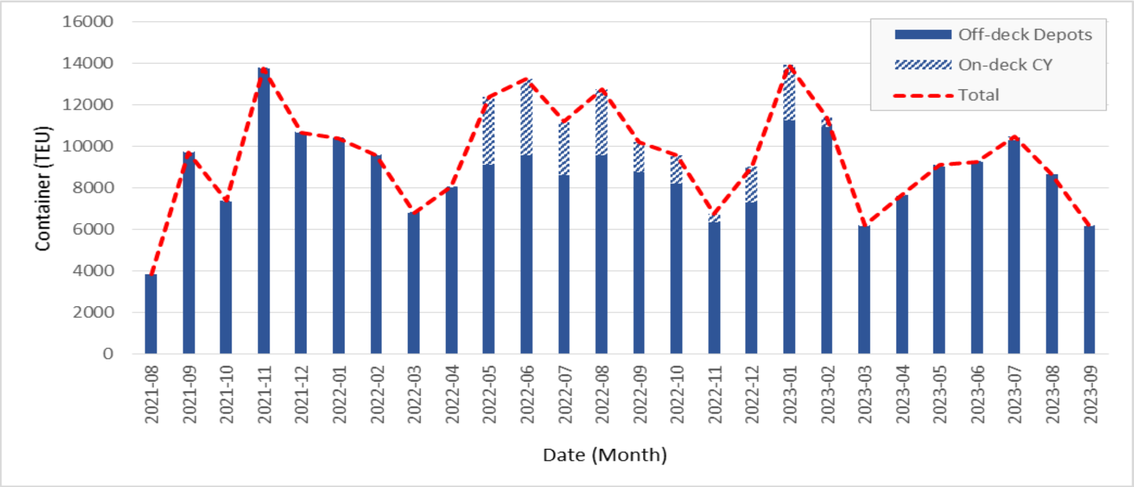

Figure 2. Monthly 20' empty container allocations to off-deck depots and CY

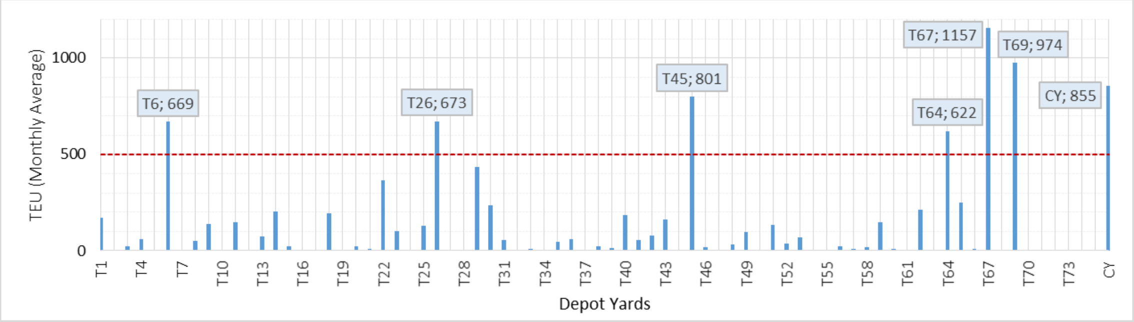

Figure 3. Monthly average demand of off-deck depots and CY

The management of empty container allocation during peak times can be improved by handling the high demand of main requesting depots. In the present study, CY and six main depots with an average monthly demand of more than 500 TEU have been selected for further investigations. The demand prediction is a prerequisite for implementing management measures to reduce the volume of daily operations and provide regular services to customers.

3.2. Methodology

With the advancement of deep learning, new models have been developed for time series prediction, among which Recurrent Neural Networks (RNNs) are considered to be one of the most effective approaches due to their feedback connections that allow information to be circulated within the network, creating a form of memory. However, the RNNs have some limitations in capturing long term dependencies for which, variations of RNNs such as Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been developed. The gating mechanism incorporated in these variations, control the flow of information and determine which data in the sequence is important to be retained and which data should be discarded. The LSTM consists of numerous memory blocks known as cells. The data flow into and out of the cells is controlled by input, output and forget gates. For a time series (X_t), the first cell uses the initial state of the network and the first time step of the sequence to compute the first output and the updated cell state. The state of the layer at each time step consists of the hidden (output) state (h_t) and the cell state (c_t). At time step *t*, the block uses the current state of the network (c_{t-1}, h_{t-1}) and the next time step of the sequence to compute the output (h_t) and the updated cell state (c_t).

The cell state contains information learned from the previous time steps. At each time step, the layer adds information to or removes information from the cell state. The layer controls these updates using *gates*. The input gate (i) controls the cell state update, forget gate (f) controls the cell state reset, cell candidate (g) adds/removes information to/from cell state and output gate (o) controls the cell state added to the hidden state. Figure 4 illustrates how the gates forget, update and output the cell and hidden states at time step *t*.

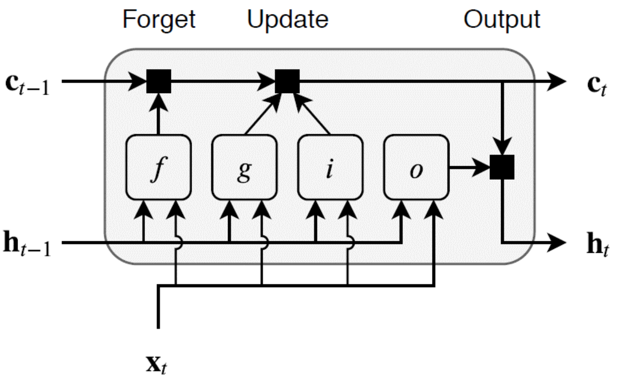

Figure 4. Data flow in LSTM at time step t

The cell state and the hidden state at time step *t* (c_t, h_t) are given by:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{1}$$

$$h_t = o_t \odot \sigma_c(c_t) \tag{2}$$

In the above equations, $\odot$ denotes the element-wise multiplication of vectors and σ_c denotes the state activation function for which hyperbolic tangent function ($tanh$) has been used. The gate functions at time step (t) are described by the following formulas:

$$i_t = \sigma_g(W_i \boldsymbol{x}_t + R_i \boldsymbol{h}_{t-1} + b_i) \quad \text{(Input gate)} \tag{3}$$

$$f_t = \sigma_g(W_f \boldsymbol{x}_t + R_f \boldsymbol{h}_{t-1} + b_f) \quad \text{(Forget gate)} \tag{4}$$

$$g_t = \sigma_c(W_g \boldsymbol{x}_t + R_g \boldsymbol{h}_{t-1} + b_g) \quad \text{(Cell candidate)} \tag{5}$$

$$o_t = \sigma_g(W_o \boldsymbol{x}_t + R_o \boldsymbol{h}_{t-1} + b_o) \quad \text{(Output gate)} \tag{6}$$

In these calculations, σ_g denotes the gate activation function for which the sigmoid function given by $\sigma(x) = (1 + e^{-x})^{-1}$ has been used.

The matrices W, R, and b are concatenations of the input weights, the recurrent weights, and the bias of each component, respectively.

This is the structure in which, the network passes important information along the sequence chain to obtain long-term dependencies and mitigate gradient related issues. The LSTM method has been employed to forecast the monthly demands of main depots based on the available datasets. Once the estimated demands for the upcoming month at main depots are determined, it is possible to send a portion of empty containers to the main depots ahead of schedule. Some of these depots even have stripped containers which are normally sent back to ECT while they can be kept if the predictions confirm the requisite. To assess the effectiveness of the proposed scenarios, ARENA software has been used for simulating the operational allocation process.

4. Demand Prediction

In the present study, 25 months of data is available. The initial 24 months of demand data for six main depots have been used for network training and testing. The training process of the network is done on 90 percent of data for adjusting the hyper-parameters to achieve acceptable validation results and the rest of data is used for testing. After training and testing the network, the demand for the 25th month is predicted and compared to the actual values as shown in Figure 5.

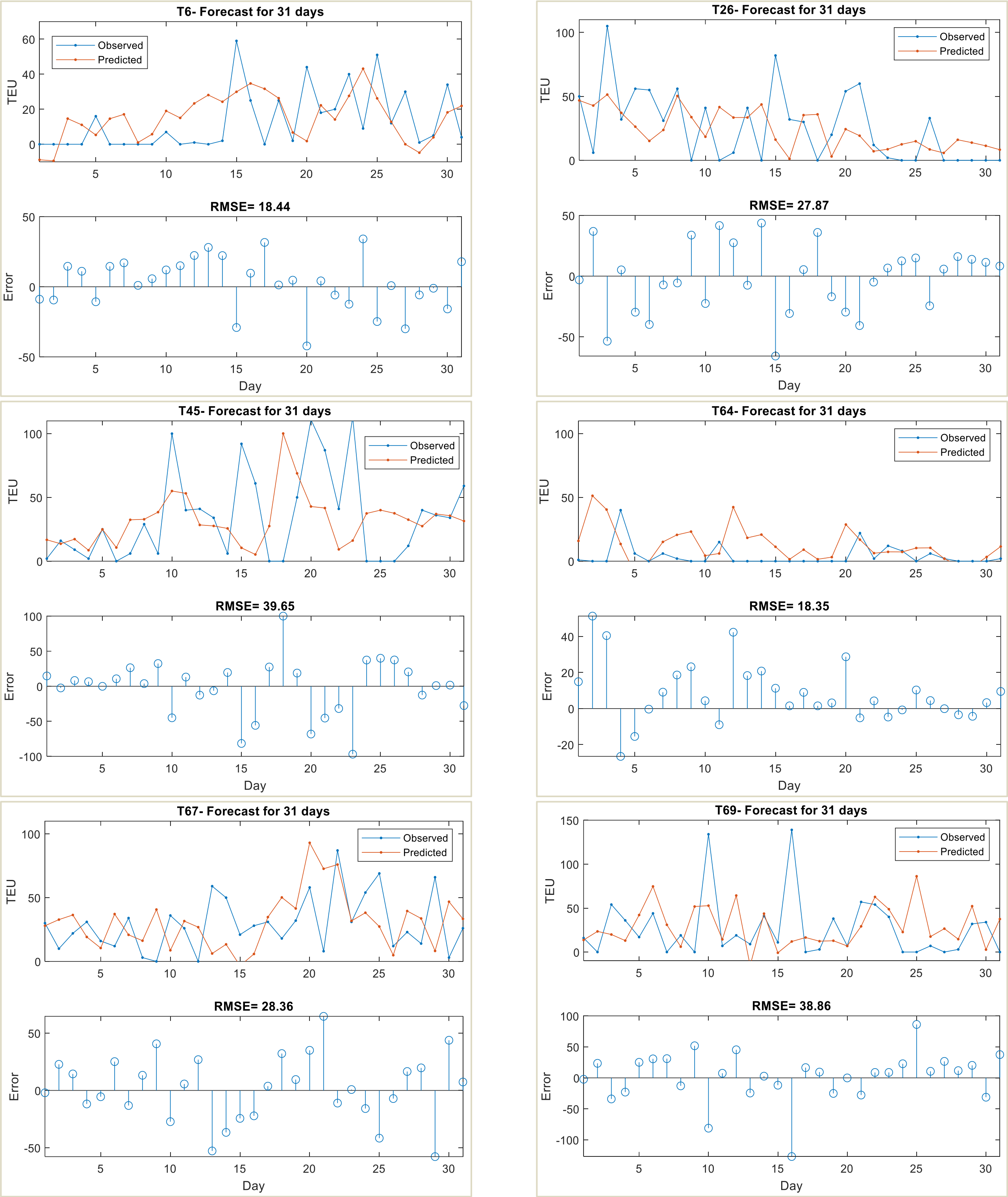

Figure5. Predicted daily demands of 25th month versus actual values for six main depots

As it can be seen in Figure 5, the daily predictions do not always demonstrate perfect alignments with actual demands which might be due to the insufficient length of the input data or the fact that the variation does not follow a regular trend and is very susceptible to different local parameters. However, the sum of daily predicted values for a month can be used as an estimation for the upcoming month's demand. The sum of daily predicted values for the last month is compared to the actual demands in Table 1 which indicates that the predictions are acceptable for most of the selected depots. However, the error is significant in case of T64 depot which could be due to its specific and coincidental circumstances. It is obvious that with the increase in the length of input data in the future, the accuracy of predictions will increase.

Table 1. The predicted versus actual demands for 25th month in six main depots

Depot ID	Actual Demand	Predicted Demand	Error (TEU)	Error (%)
T6	405	477	72	18
T26	804	741	-63	-8
T45	1052	987	-65	-6
T64	124	385	261	210

T67	910	963	53	6
T69	821	896	75	9

5. Simulation of Empty Container Distribution

Knowing the approximate demand of main depots, it is possible to send a portion of demand ahead of the schedule during off-peak times, or utilize stripped empty containers available at the demanding depots. To assess the effectiveness of this approach, ARENA software is used for simulating the operational empty container allocation process in September 2023. Three scenarios have been considered for the simulation as explained below:

i. In the first scenario, the normal condition based on the actual demands of September 2023 is simulated.

ii. An abrupt increase in the CY demand is added to the normal condition. Total demand of 2000 TEU is considered for CY.

iii. In this case, it is assumed that half of the predicted demand for six main depots and CY are pre-sent during off-peak times. The rest of the demand for these depots are kept in the simulation.

Figure 6 shows that a limited number of depots allocate the significant volume of the demand and the share of other depots is negligible. In September 2023, 99.4 % of the total demand was allocated by 30 depots out of 75 depots. In the simulation process, these 30 depots are considered. The distance from ECT to demanding depots and their monthly demands in different simulation scenarios are shown in Table 2.

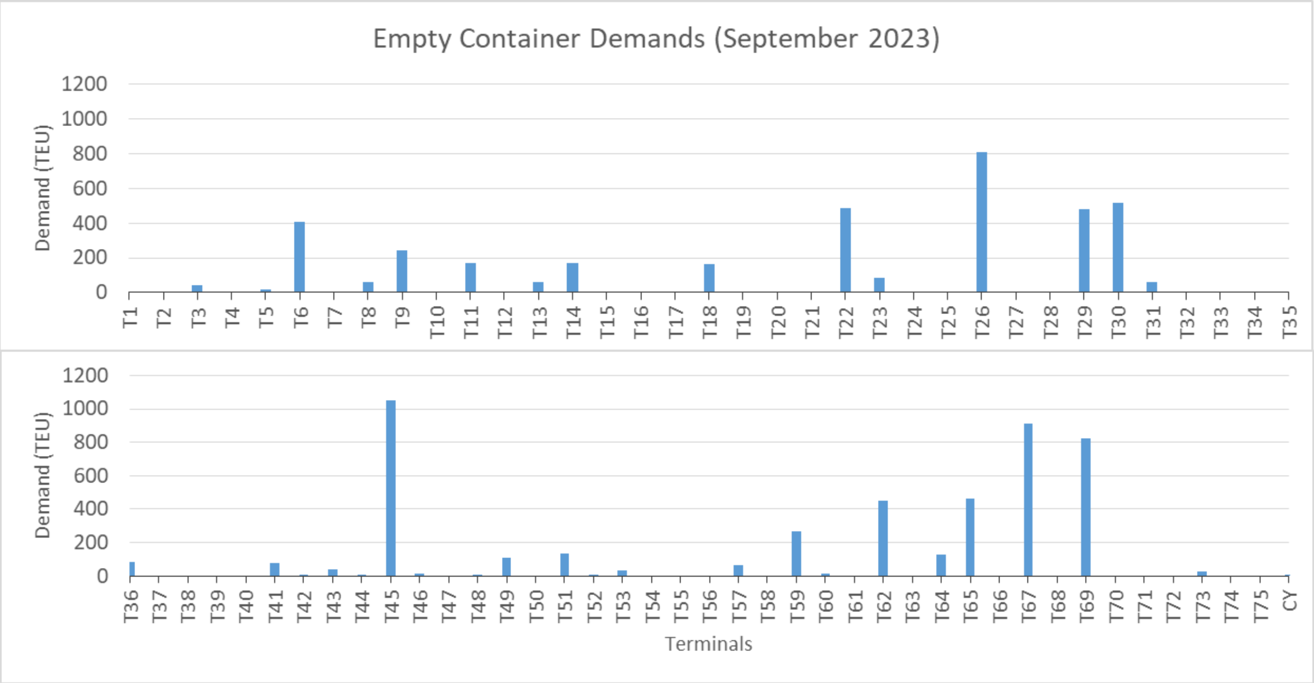

Figure 6. Depots' empty container demands in September 2023

Table 2. Depots' demands in in September 2023 in three simulation cases [12]

Depot	**Distance from ECT (m)**	**Demand (TEU)**		
		Scenario 1	**Scenario 2**	**Scenario 3**
T3	3000	40	40	40
T5	3000	20	20	20
T6	4000	405	405	167
T8	3000	58	58	58
T9	4000	245	245	245
T11	3300	172	172	172
T13	3000	60	60	60
T14	1500	169	169	169
T18	2400	161	161	161
T22	1700	483	483	483
T23	3000	84	84	84
T26	3400	804	804	434
T29	3400	477	477	477
T30	2000	513	513	513
T31	3000	62	62	62
T36	3000	85	85	85
T41	3000	74	74	74
T43	3000	37	37	37
T45	3700	1052	1052	559
T49	2000	108	108	108

Depot	**Distance from ECT (m)**	**Demand (TEU)**		
		Scenario 1	**Scenario 2**	**Scenario 3**
T51	1300	136	136	136
T53	3000	31	31	31
T57	3000	64	64	64
T59	2700	263	263	263
T62	300	448	448	448
T64	3700	124	124	0
T65	2300	463	463	463
T67	1200	910	910	429
T69	1700	821	821	373
T73	3000	25	25	25
CY	2500	4	2000	1000
Total	-	8398	10394	7240

In the simulation process, it is assumed that enough empty containers are always available at ECT. Based on the registered and approved monthly demand of requesting depots, their exclusive trucks are called to refer to ECT for picking up the empty containers but for sending empty containers to the CY, ECT trucks are used. Each truck has the possibility to move two TEU at the same time, so in the simulation, each input entity is equivalent to two TEU. Hence, the number of entities entering the system is considered to be half of the demand. It is assumed that two staff members at ETC are in charge of executive operations, who carry out the load-on services of empty containers onto trucks during 12 working hours per day (day shift). The time required to load each truck is assumed to follow a triangular distribution with minimum, maximum and average of 2, 10 and 6 minutes respectively. The number of trucks sent by each depot is different. Based on field surveys, each depot uses an average of five trucks to transport empty containers. The number of ECT trucks for sending empty containers to the CY is 14. The speed of trucks in the port area varies between 20 and 60 km/h, which depends on the travel time and the amount of traffic on the internal roads. In this study, the traffic information of the area was not available and the approximate speed of the trucks was assumed to be 40 km/h. In the destination depots and CY, two personnel are considered to unload the trucks, who perform the executive operations with a triangular distribution similar to the loading stage. The operational steps of empty containers distribution and the simulation model are shown in Figure 7 and Figure 8 respectively.

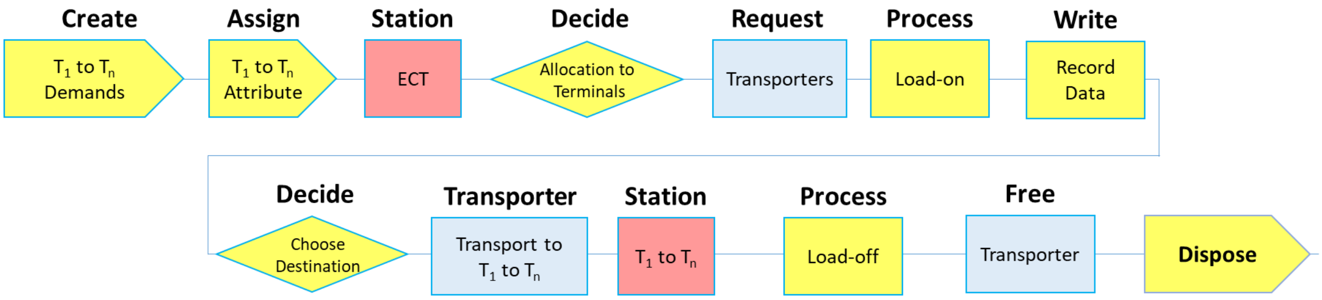

Figure 7. Operational steps of empty containers distribution

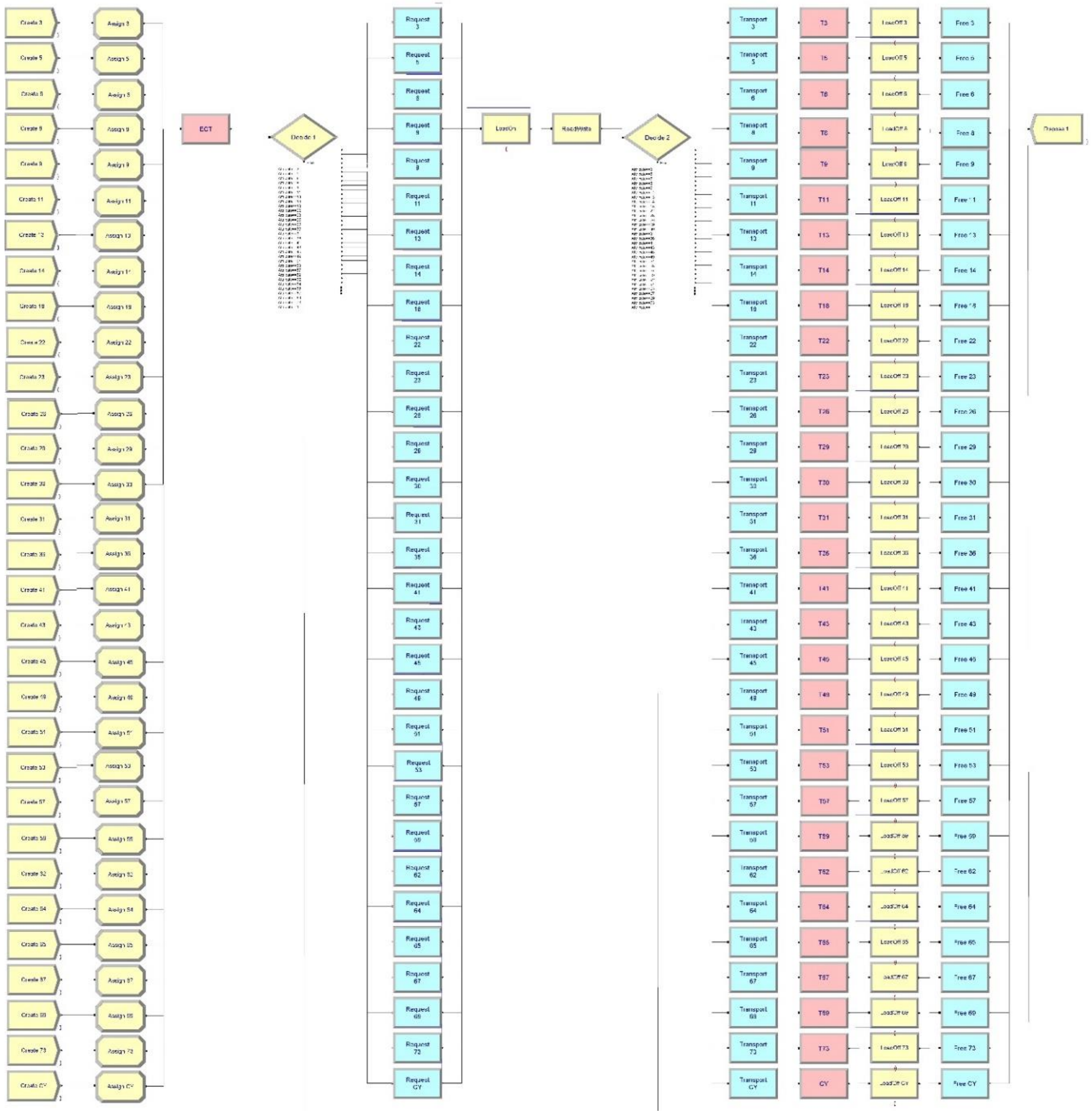

Figure 8. ARENA simulation model for empty containers distribution

In the first scenario regarding the normal condition in September 2023, the total actual demand is 8398 TEU for which 4199 entities have entered the system. Considering that two executive agents at each depot can load-on two trucks simultaneously and each truck requires a minimum loading time of two minutes, the whole distribution time cannot take less than 70 hours. However, considering that the time required to load on each truck is assumed to follow a triangular distribution with an average of 6 minutes, the optimal average operational time would be around 210 hours.

In the initial modeling, the number of allocated transporters (trucks) to each demanding depot was considered unity. The average time for delivering all the entities to the destination depots was approximately 288 hours (24 working days). As mentioned previously, based on field surveys, each depot yard uses an average of five trucks to transport empty containers and 14 trucks are usually used by ECT to deliver empty containers to the CY. So, in the next step, the number of available transporters increased to the mentioned values. The results show that the total time required to deliver all the empty containers reduces to 213 hours (18 working days). Further increase in the number of trucks did not have a meaningful effect on the total operational time. The only consequence would be an increase in traffic and queue length at ECT for load-on process. It can be concluded that the number of trucks used by the depots for delivering empty containers is almost optimum.

In the second scenario, an abrupt increase in the demand from the CY is added to the normal condition. The CY demand (which was actually 4 TEU in the desired month) is increased to 2000 TEU and consequently the total demand in this condition reaches 10394 TEU (5197 input entities).

The total time required to deliver all the empty containers in this case has increased from 213 hours (18 working days) to 262 hours (22 working days).

In the third scenario, it is assumed that half of the predicted demand for six main depot yards (section 4) is sent ahead of schedule during off-peak times. The rest of the demands for these depots are kept in the simulation. It is also assumed that half of the CY demand (1000 TEU) is pre-sent and only 1000 TEU is considered as CY demand. Consequently, the total empty containers to be sent have reduced from 10394 TEU to 7240 TEU (30% reduction). These results show that the total delivery time has also decreased from 262 hrs. (22 working days) to 183 hrs. (16 working days). The main results of the simulations are presented in Table 3.

Table 3. Main simulation results

Item	Scenario			Unit
	1	2	3	
Total Simulation Time	212.6	261.9	183.3	hours
Total Wait Time (Maximum)	212.5	261.8	183.2	hours
Total Transfer Time (Maximum)	0.1	0.1	0.1	hours
Load On Wait Time Per Entity (Maximum)	7.58	8.07	7.86	hours
Load On Wait Time Per Entity (Average)	3.21	3.70	4.23	hours
Load On Queue Waiting Time (Maximum)	7.48	8.01	7.76	hours
Load On Queue Waiting Time (Average)	3.11	3.6	4.13	hours
Load On Queue Number Waiting (Maximum)	148	161	156	Number
Load On Queue Number Waiting (Average)	62	71	82	Number
Load Off Wait Time Per Entity (Maximum)	0.23	0.25	0.25	hours
Load Off Queue Waiting Time (Maximum)	0.08	0.15	0.15	hours
Load Off Queue Number Waiting (Maximum)	2	3	3	Number
Load Off Queue Number Waiting (Average)	0	0	0	Number

The results indicate that the maximum transfer times in all scenarios are negligible compared to the waiting time at load-on queue. Hence, increasing the number of trucks or the assumed velocity does not affect the results considerably. This is important from the viewpoint of resource allocation management and traffic control measures. It is also remarkable that the waiting time in load-on process is considerable at ECT where all the trucks sent by requesting depots shall pass through a shared queue. On the contrary, the load-off processes at different depot yards do not lead to significant queues or noticeable waiting times. Although the entire distribution and transportation operations can be completed within a month, the length of the load-on queue and the associated average waiting times are significantly high in all the scenarios indicating the importance and necessity of management measures.

The daily variation of load-on queue length and average waiting time for different scenarios are shown in Figure 9 and Figure 10. The trends show that in case all the requesting depots send their trucks simultaneously to pick up the empty containers, a long queue is formed at ECT at the beginning of the month and the average waiting time of trucks in the load-on queue reaches 4 to 5 hours.

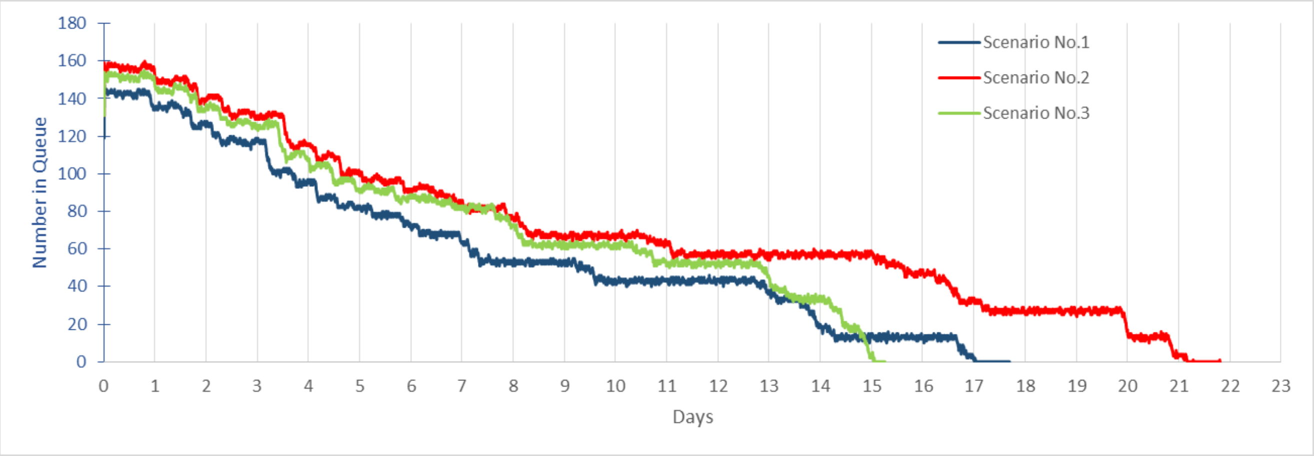

Figure 9. Daily load-on queue length for different scenarios

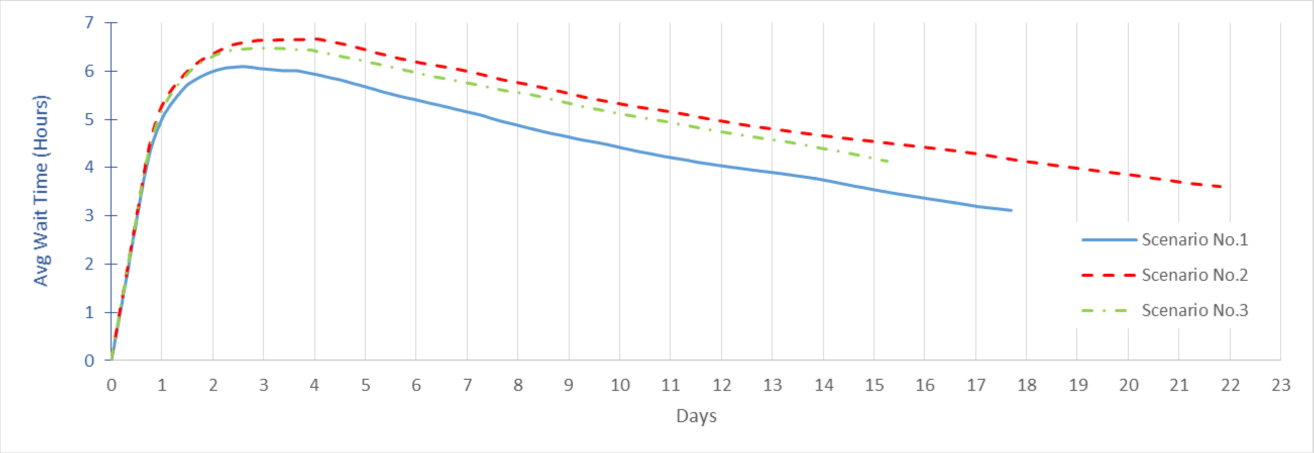

Figure 10. Average waiting time in load-on queue for different scenarios

One solution for reducing the queue length and waiting time is the asynchronous calling of the trucks from different depots on a pre-scheduled plan. Such schedules can be planned and checked through simulations. As an example, an asynchronous schedule is planned for the first scenario and the resulting queue length and waiting times are compared to the case of simultaneous call of trucks. As it can be seen in Figure 11 and Figure 12, while the entire operational time has remained 18 days, the max number in load-on queue has decreased from 147 to 13 (91% reduction) and waiting times has decreased from 6 to 0.5 hrs. (92% reduction). Although this approach is found to be very useful, it should be applied with caution and based on operation simulations since blind scheduling may result in extension of the overall operational duration.

The results including the similar scheduling for the second and the third scenarios are shown in Figure 13 to Figure 16 and Table 4.

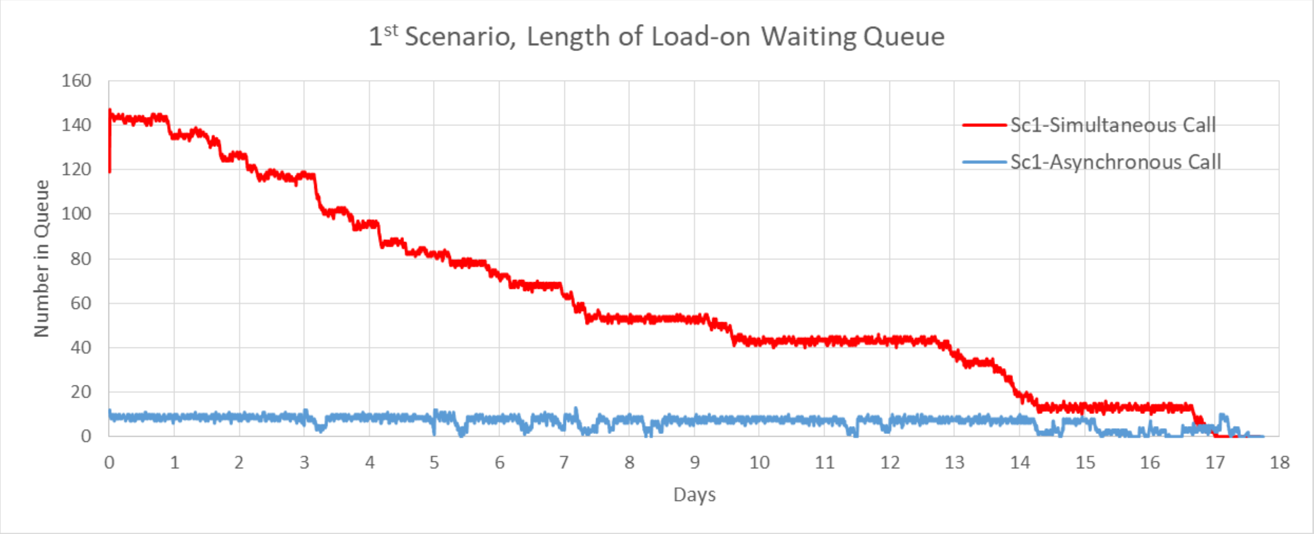

Figure 11. First scenario queue length, simultaneous versus asynchronous call of trucks

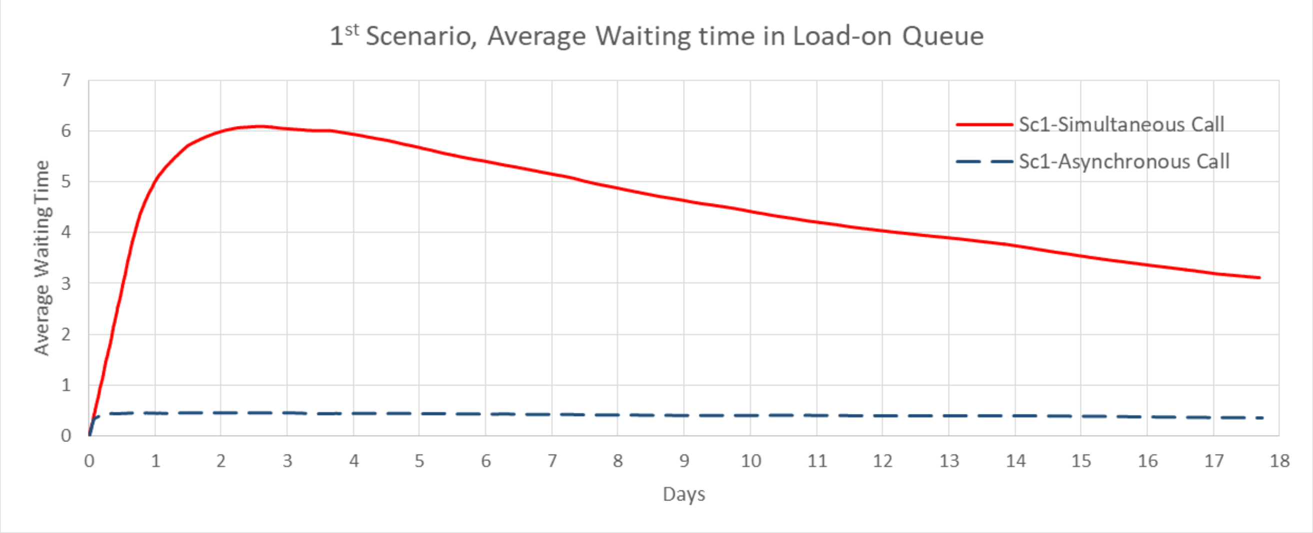

Figure 12. First scenario average waiting time, simultaneous versus asynchronous call of trucks

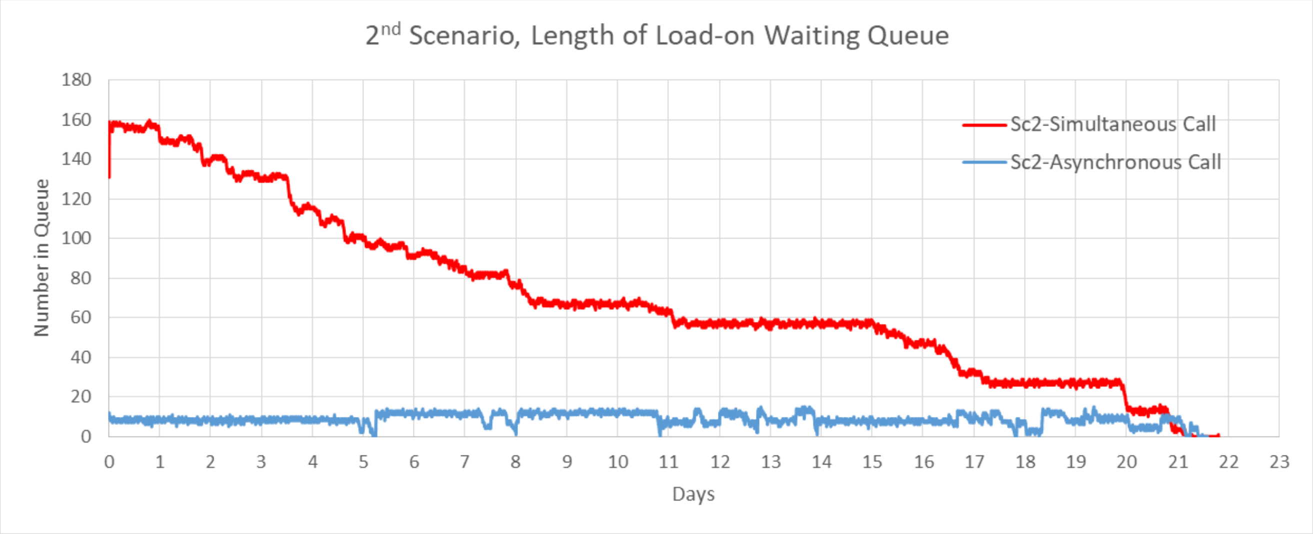

Figure 13. Second scenario queue length, simultaneous versus asynchronous call of trucks

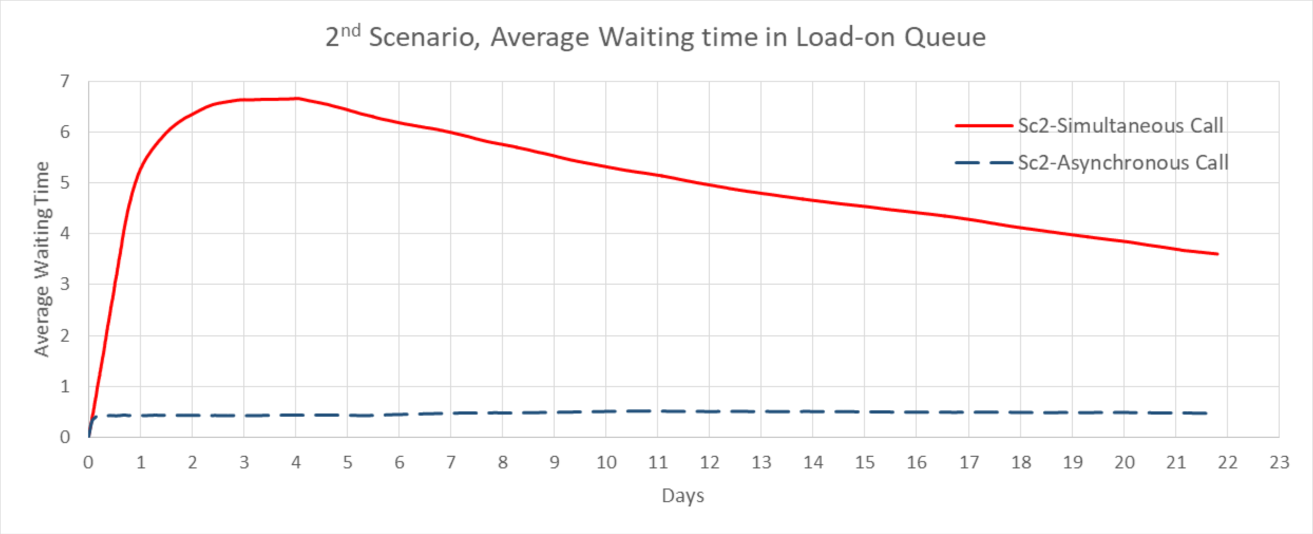

Figure 14. Second scenario average waiting time, simultaneous versus asynchronous call of trucks

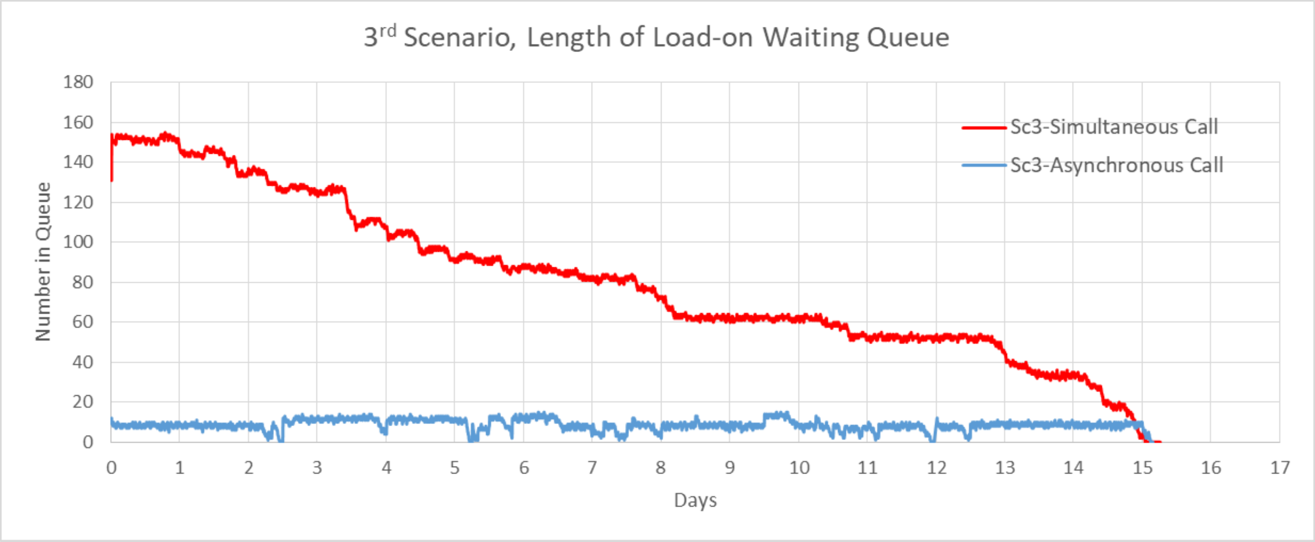

Figure 15. Third scenario queue length, simultaneous versus asynchronous call of trucks

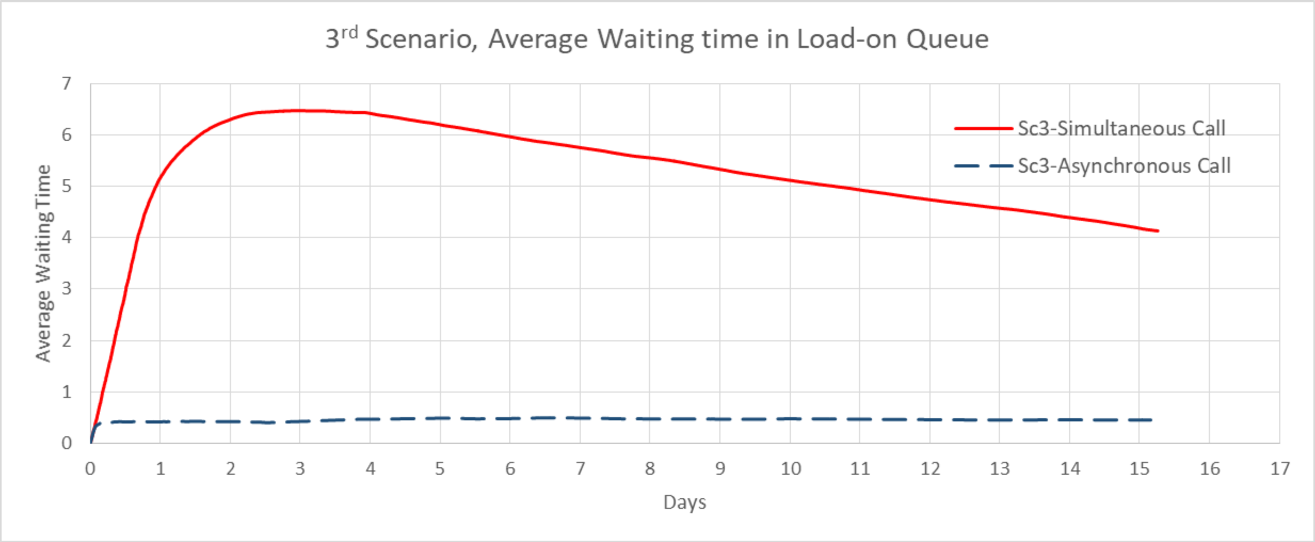

Figure 16. Third scenario average waiting time, simultaneous versus asynchronous call of trucks

Table 4. Load-on queue condition, simultaneous versus asynchronous call of trucks

Item	**Call of Trucks**	**Scenario**		
		1	**2**	**3**
Total Load-On Queue Time (hrs)	Simultaneous	212	262	183
	Asynchronous	213	259	182
	Difference %	***0.5***	***-1.1***	***-0.5***
Max Number in Load-On Queue (Number)	Simultaneous	147	160	155
	Asynchronous	13	15	15
	Difference %	***-91.2***	***-90.6***	***-90.3***
Peak of Average Waiting Time in Load-On Queue (hrs)	Simultaneous	6.1	6.7	6.5
	Asynchronous	0.5	0.5	0.5
	Difference %	***-91.8***	***-92.5***	***-92.3***

It is observed that while the entire operational time is kept almost constant, the scheduling of truck calls has led to a considerable decrease (around 90%) in queue lengths and average waiting times.

6. Conclusion

In this paper, the optimization process of empty container operations in Shahid Rajaee Port of Iran has been investigated using machine learning and simulation tools. Management of empty containers delivery to demanding depot yards and vessels is rather complex in this port, especially when high demands arise from container yard for loading empty containers on vessels. The demand history was available on a daily basis for 25 months. Although the empty containers are sent to almost 75 demanding depots, the records show that the majority of demand was dedicated to a limited number of them. Six main depots with an average monthly demand of more than 500 TEU as well as container yard have been selected for demand prediction using Long-short-term-memory neural network. The daily predictions did not always demonstrate perfect alignments with actual demands due to insufficient data, but the sum of daily predicted values gave a good estimation for a month. Knowing the approximate demand of main depots, it is possible to send a portion of monthly demand ahead of the schedule during off-peak times, or utilize stripped empty containers available at the demanding depot. To assess the effectiveness of this approach, the operational empty container allocation process in September 2023 was simulated. The normal condition based on the actual demands was first simulated. Then, an abrupt increase in the CY demand was added to the total demand. Eventually, half of the predicted demand for six main depots and the CY was subtracted from the model assuming that it was sent to the depots ahead of schedule during off-peak hours. The simulations revealed that the load-on process at ECT is the operational bottleneck. The transfer time and load-off operations at destination depots do not have a significant effect on the total operational duration. Early demand prediction of only six depots as well as the CY and providing half of the predicted demand ahead of the schedule can reduce the total operational time up to 30%. However, such remedies do not have any positive effect on reducing the maximum queue length or average waiting times. The simulation results have shown that the depots’ trucks should not be called simultaneously upon demand confirmation at ECT. Planning a schedule for asynchronous call of trucks to pick up the requested empty containers can reduce the queue length and average waiting time up to 90%. Although an asynchronous call of trucks has been found to be highly effective in reducing the queue length, it cannot be used randomly and without a precise plan since it may lead to the extension of the overall operational duration.

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