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On-line cross docking: A general new concept at a container port

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Abstract. Cross docking is one of the innovation product distribution strategies for transhipment of time-sensitive products in distribution centers which has absorbed a lot of attention in the last 10 years. The current study develops a new concept named "on-line docking" in an actual container port which is the main contribution of the research. In the model, some previous simplifications were removed from the model using optimization via simulation technique, and also new decision variables were introduced to control the system. The objective function is to minimize the average annual system costs by assigning the best number of inbound-outbound docks and the fleet size for the internal transportations. To do so, all information was taken from an actual container port system and the model was built in the simulation software and then it was optimized via a meta-heuristic algorithm. The computational results show the efficiency of the proposed approach in real world applications.

1. Introduction

To remain competitive in the market, companies try to make their operations more efficient and effective. One of the strategies to improve the efficiency of distribution in logistics is cross-dock (CrD) [1]. The main advantage of implementing cross-docking is that the products can be sent more quickly to the customers compared to traditional warehouse. It can save the distribution time and cost, shorten the delivery cycle time, and improve the customer satisfaction [2]. With a good schedule, the products can be delivered on time so as to meet the customer requirements. Effective plan for the vehicle routing of cross-dock can minimize the route of delivery and maximize the number of full truckload (FTL) so the transportation cost can be minimized. According to Material Handling Industry of America (MHIA), CrD is the process of moving merchandise from the receiving dock to shipping dock without placing it first into storage locations and it is a subset of the Supply Chain Network concept [3]. This concept requires a very good synchronization between incoming (inbound) and outgoing (outbound) vehicles, (trucks) and it is clear that a perfect synchronization is very difficult to achieve due to the stochastic nature of the actual system; for example, the arrival times of inbound loads may not be fixed or even the travelling time of outbound trucks from the docks to the customers and their return may not also be fixed. That is why many authors have neglected such a restriction from the concept [4]. So a CrD concept can be expressed as the process of consolidating freight which comes from several origins, with minimal handling and with little or no storage between incoming and outgoing goods. The concept has the following advantages [5]:

- Cost reduction in inventory holding costs and labor costs;

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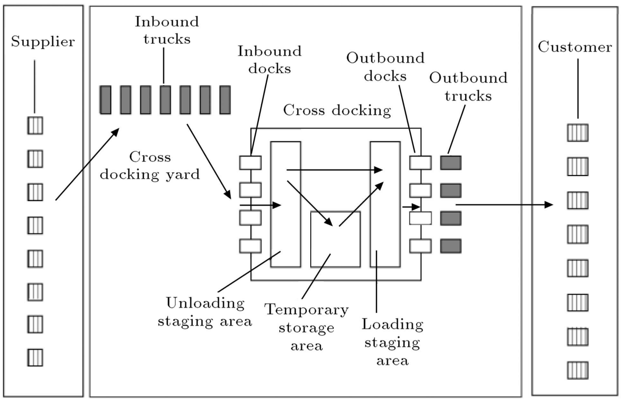

Figure 1. The concept of a CrD system.

- Improving the customer service process by shortening the delivery time;
- Reduction in storage area;
- Faster inventory turnover;
- Reducing the risk of damaged or lost items.

Figure 1 depicts the concept of a CrD system where it has several inbound and outbound docks.

A CrD terminal has several characteristics which must be considered by a practitioner. The first one is the number of touches (stages). In a one-touch CrD, products are touched only once, i.e. they are loaded on an outbound truck at stack doors (doors assigned to outgoing loads) whenever they arrives at strip doors (doors assigned for inbound loads) and is the pure CrD [5]. But in a two-touch or single-stage CrD, products are received at strip doors, staged on the dock until they are loaded for outgoing transportation. Depending on assignment of a customer to an individual load, the problem can be divided into two main categories: pre-distribution and post-distribution CrD. In pre-distribution scheme, the customer is known and assigned by the supplier before arriving in the CrD, but in the second version, the customer is assigned at the CrD system. The next characteristic of a CrD system is the physical shape of the system. Most authors and practitioners have used a narrow rectangular shape for the system (I-shape) but there are other shapes such as L, U, T, H, and E [5]. Number of dock doors has a significant influence on the system performance and may vary from 1, 2, ..., 200 doors. Other important characteristics are as follows:

- Internal transportation system: The system related to activities at the CrD which can be done manually by the workers or by automated facilities or a combination of both methods;
- Service mode: According to Boysen and Fliender [5], the service mode defines the degrees of freedom in assigning inbound and outbound trucks to dock doors. In exclusive mode, each dock door is either assigned to inbound or outbound trucks. In the mixed mode, all dock doors can process all types of trucks;
- Arrival pattern: The arrival time of loads may be fixed or stochastic and has a great influence on the congestion of the system and also on the scheduling of workers and other resources;
- Departure time: The trucks' departure time could have a restriction. In some cases, it is important for all trucks to leave the system before a predefined time;
- Temporary storage: In practice, the loads are staged at the CrD floor after receiving in front of stack doors. It is also possible that there will be no such facility at the CrD system.

2. Literature review

CrD researchers must deal with several decision variables which have a serious impact on the system performance. The location of a CrD is a part of distribution network design which identifies the position of the docks. Sung and Song [6] considered a CrD system from the suppliers to the customers by minimizing the total costs via setting different CrD locations. The demand rate and incoming load plan were supposed to be known before scheduling and they used integer programming to solve the model. Sung and Yang [7] developed the solving algorithm in [6] using Tabu search meta-heuristic algorithm. Bachlaus et al. [8] considered a multi-echelon supply chain network to optimize the material flow in the supply chain and also the number and location of suppliers, plants, distribution centres, and CrDs. They used a multi-objective mathematical model to minimize the total costs and maximize the volume flexibility using Particle Swarm Optimization (PSO) algorithm. Once the location of a cross-dock is determined, another decision is to select the layout, including the dimension and the shape of the internal areas and their arrangement. Gue and Kang [9] investigated the queue behaviour at the strip and stage doors using simulation technique. They showed that for a single-stage storage area, shorter lanes act better than long ones, and also the fact that a two-stage CrD system behaves significantly lower than a single stage one. Some researchers do not consider just a single CrD system, but verifying a network framework. The target is to reduce the total costs through the entire network by adjusting the appropriate flows. Ma et al. [10] presented an integer programming model in a Shipment Consolidation Problem (SCP) where supplier and customer time windows and also the transportation times among the nodes were considered. They showed that the model is NP-Complete and tries to solve it by Genetic Algorithm (GA). In a CrD, when the loads arrive at strip doors, a new problem arises in order to find the best (usually the quickest) way from the inbound to the destination at outbound docks. The problem is similar to so-called Vehicle Routing Problem (VRP). Wen et al. [11] investigated the VPR at a CrD without temporary storage capacity. They used a mixed integer programming model to tackle the problem and used Tabu search method to solve it. Another attractive problem for the researchers is the Truck Scheduling Problem which deals with where and when the trucks should be processed at each dock door. McWilliams et al. [12] studied the problem of inbound trucks at a CrD in the parcel industry. The incoming loads were transporting to the outbound trucks via some conveyors and the target was minimizing the makespan (the time between the arrival time of the first parcel load to the time of loading the last one at the outbound dock). They used a simulation-based scheduling method in their research because they could not analyze the queue behaviour at each conveyors using typical analytical methods. They also used a GA algorithm which used the details of their deterministic simulation model. However, they used a simulation-based approach but did not benefit from the powerful approach in modelling the stochastic complicated processes. Simulation technique is one of the best tools to deal with the actual large scale problems where there are a lot of non-linear relations with stochastic events. They continued the study until 2010 by issuing a new paper [13] which solved their previous model using a decomposition approach. The Optimization Via Simulation (OVS) technique, which they used at first study, was based on traditional methods in OVS, so they could not progress the solutions in large scale problems. Therefore, the decomposition algorithm was developed. In traditional versions of OVS algorithm, for any improvement at the objective function or even when it is needed to evaluate the fitness function for a solution, the simulation model must be replicated several times which leads to more computational times. In modern OVS methods, the Response Surface Method (RSM) or/and a meta-heuristic approach is combined with OVS method to make it more efficient [14]. According to [4], one of the most important shortcomings of previous researches in CrD systems is related to deterministic assumptions made on inbound arrival times and also in travel time of outbound trucks. There are several events in real world applications which cause the system to behave stochastically, such as inbound and/or outbound truck failures and therefore the probabilistic repair times, probable traffic jams, suppliers' delay which leads to non-deterministic arrival plans and so on. Therefore, developing new modelling techniques which cover such natural behaviours are inevitable. Azimi [15] developed a general OVS algorithm and showed its performance in 3 classes of combinatorial problems. However, the proposed algorithm could be used in other problems which have 0-1 decision variables. In another research [16], he showed the use of an OVS algorithm in Assembly Line Balancing Problems. However, a brief review of recent developments in OVS modelling and solving methods has been presented by [14].

In this paper, the idea of a CrD has been developed to a real world application at a local container port in southern part of Iran near the mouth of Persian Gulf which trades goods and is connected to more than 80 well-known ports throughout the world. Terminals 1 and 2 with the storage capacity of 168,000 TEU (Twenty Equivalent Unit) are able to do 3,100,000 TEU container operations a year in this port.

A Container Terminal (CT) is a place where ships can be berthed near the quay and can give some services to vessels by Gantry Cranes (GC). The given services include: unloading the container from the vessel or loading the container on the vessel. A container terminal usually makes the connection between the sea and the possible land. Also, container terminals can be viewed as a temporary storage area, so the containers can be kept there from the time of unloading until the moment of delivery to the customers. Container ports have a great role in modern transportation systems [17,18]. According to [18], the average annual growth in container ports will reach to 10% by 2020 while the growth will be just 2% for other means of transportation. This fact shows the importance of container ports in the global trade system. A review of previous researches shows that the majority of studies have used queuing theory as a method for estimating the performance of the port system Kozan [19]. On the other hand, these studies have made some special assumptions to simplify the real world problems [20]. For example, many researches only considered a single queue model for the internal operations while in a real port, there are several queue networks which increase the complexity of the problem and decrease the power of analytical methods like queuing theory in solving such problems. Another usual simplification made in such cases is assuming the stochastic distribution function of all events as negative exponential, due to its memory less property which makes the model much easier, while there are several evidences that many real world events do not follow this type of probabilistic pattern. Lee et al. [21] addressed a yard storage allocation problem in a transhipment hub with the objective of reducing reshuffling and traffic congestion. They aim to assign containers to sub block locations as well as yard cranes to blocks and propose a mixed integer linear programming model which minimizes the number of cranes needed to handle the total workload. Lee and Hsu [22] presented a model for the container re-marshalling problem: in order to utilize yard space more efficiently and speed up loading operations, they propose to re-marshal containers in such a way that they fit the loading sequence. The problem is modelled as a multi-commodity flow with side constraints: The model is able to re-position export containers within the yard, so that no extra re-handles will be needed during the loading operations. According to the best knowledge of the author, there is no previous similar research to develop a CrD concept in the container ports, the idea which will outstand the CrD concept to be used in large scale real world applications. In the current study, the system definition is explained in Section 3. The simulation model is explained in Section 4, including the new CrD concept. In Section 5, the general OVS approach is presented based on GA. The computational results are summarized in Section 6, and finally, the conclusions are explained in Section 7.

3. System definition

A Container Terminal (CT) is a place where ships can be berthed near the quay and can give some services to vessels by Gantry Cranes (GC). The given services include: unloading the containers from the vessel or loading the container on the vessel. CTs can be viewed as a temporary storage area, so that the containers can be kept there from the time of unloading till the moment of delivering to the customers. Therefore, the unloaded container from the vessels by GC should be transferred to suitable places in the yard. To do so, the containers in the real system are loaded on some internal trucks after unloading in order to be transported to the Container Yard (CY). With respect to the fact that the unloaded container is import (IM), refrigerator (RF), tranship (TR) or empty (EM), it should be moved to the related blocks determined in the CY. As soon as the trucks arrive at the CY, other equipment called Rubber Tyred Gantry Cranes (RTGC) start unloading trucks and arrange the containers in predefined blocks. As mentioned before, a container may be kept in the CY from one hour to several days, and then it is taken away from the CY either to be loaded on the vessel or to be delivered to the customers. TR containers are the ones which are usually unloaded from bigger ships in the terminal and reloaded on other ships that depart toward other container terminals in or out of country.

The problem starts when a vessel arrives at the port berth and a part or the entire part of its load has to be unloaded. The first action is to unload the loads by GCs and transferring them to a temporary storage area called "Marshalling Yard" by trucks. At this stage, they are temporarily stored on two main Blocks in a random base by RTGCs. At the MY, the final location of a container is set and labelled according to its type and the available spaces at the yard. Finally, they will be sent to the final storage area at the Yard by trucks. The Marshalling Yard (MY) is a buffer used in many actual container ports to ease the process of transmitting the loads from the vessel to the yard, because there are some stochastic events which cause a possible delay on unloading/loading of a ship, such as any malfunction on the cranes and/or in trucks, traffic jams, and arriving rate of ships at the berth. These natural events will cause more delays which means more average system time for the ships at the berth or the ships on the queue. According to international standards, a ship which has more than 5 hours stay at a port must be paid a penalty by the port. So, it is very important for the port managers to control the average system waiting time at their port to avoid the penalties. According to the current information, the port has paid around USD 2.36 m in 2010 as penalties when they did not have the MY. But, when they created the area, the penalty costs reduced to USD 0.91 m in 2011 and USD 1.01 m in 2012. Figure 2 depicts the layout of the current system.

4. New system model

In this section, the main idea is to develop the docking concept to the port and then constructing the simulation model to analyze the system by introducing a new concept named on-line CrD system. The MY area - a temporary area which is used to avoid possible delays in serving the ships - is the main docking terminal for the study. It has 2 available docks (similar concept of a dock) for inbound trucks and 2 ones for outbound trucks. On each dock, there is a RTGC together with a worker to serve the trucks. Since the arrival time of the ship is stochastic and there are possible traffic jam between the berth and MY, then the arrival rate of inbound trucks is stochastic too. Also, for outbound trucks, the time when they leave the MY to come back again is stochastic due to any possible failure in trucks

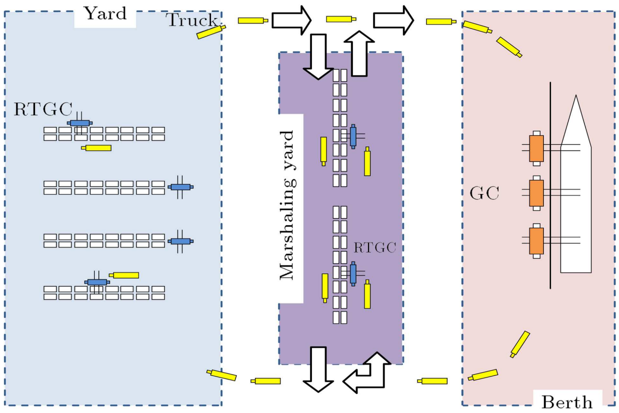

Figure 2. The schematic diagram of underlying actual system.

and any possible traffic jams between the MY and the yard.

4.1. New decision variables

Concerning the decision variables, it is very important to categorize the analytical approaches used by researchers into two main groups: "on-line" and "off-line" approaches. An approach is called off-line when the arrival times of inbound trucks and the travelling times of outbound trucks are known in advance and so the decision variable could be the scheduling of docks. Nearly all previous studies used such an approach to analyze docking systems, except just one research [13]. It is clear that taking such an assumption is not a realistic one. On the other side, an on-line approach is the one which assumes all important events are stochastic. Therefore, the scheduling of a dock could not be a decision variable. In an on-line approach, the decision variables are:

- The controlling rules including the pickup/delivery/ dispatching/selection strategies;
- The fleet size of inbound/outbound of trucks;
- The number of inbound/outbound docks;
- The internal transporting system;
- The layout of the model.

In the current study, the last decision variable has not been considered and the focus was concentrated on the first 4 decision variables. According to the current sequence, when an incoming truck arrives at the docking for unloading, it must be assigned to one of the available docks. A delivery strategy is the policy of assigning an incoming truck to one of the two available inbound docks. These strategies could be defined as follows:

- The smallest queue length for an inbound dock (SQLI): This strategy always assigns the trucks to a dock which has the smallest queue length of waiting trucks;
- The smallest utilization rate for an inbound dock (SURI): This strategy always assigns the trucks to a dock (RTGC) which has the smallest utilization rate (or having more idle time).

On the second step, when an incoming truck is unloaded and the loads are staged at YD, the system assigns 3 labels on each container including the customer code, container type, and its due date. At the system, the container type is not important at MY and all containers are assigned randomly in the current two blocks (each block has a capacity of 5000 containers in two levels). Now, we have a new problem and it is the next action for the internal lift trucks at the MY which is called selection rule. This rule defines that an idle lift truck must serve to an inbound dock (taking the loads from an inbound dock and storing it at the MY) or pick up a staged load and deliver it to an outbound dock.

- First to Serve an Inbound Dock (FSID);
- First to Serve an Outbound Dock (FSOD);
- First to serve the one which has the maximum total waiting time of loads (FSMW);
- First to serve the one which has the longest loads queue (FSLQ).

On the third step, when a lift truck wants to serve a specific outbound truck it must select and pick up a load from the storage area at MY which is called a pickup strategy. The possible strategies could be:

- Selecting a load with largest waiting time (SLWT);
- Selecting a load with maximum total lateness time (SMLT);

And finally, on the fourth step, a dispatching strategy has the same meaning as a delivery strategy for an outbound truck when it arrives at an outbound dock:

- The Smallest Queue Length for an Outbound dock (SQLO): This strategy always assigns the trucks to a dock which has the smallest queue length of waiting trucks;
- The Smallest Utilization Rate for an Outbound dock (SURO): This strategy always assigns the trucks to a dock (RTGC) which has the smallest utilization rate (or having more idle time);
- The Largest Loads Waiting Time (LLWT): This strategy always assigns the trucks to a dock which has the largest summation of loads waiting times;
- The Largest Loads Lateness Time (LLLT): This strategy always assigns the trucks to a dock which has the largest summation of loads lateness times.

In all strategies, when a tie up situation occurs, the system selects a decision randomly. In Table 1, the decision variables defined for the control strategies have been listed in 4 levels. Each level is related to a decision variable (a control strategy) in 2 or 4 different levels. For example, the selection strategy has 4 possible strategies. However, one may add or delete some levels for each strategy according to the special characteristics of the problem. Therefore, total strategies are 64 ones, i.e. there are 64 different possible solutions (Table 2). To simplify the solution names, a special notation is used here. For example, a solution named "1322" is related to the dock controlling rules, where the delivery rule is set to "SQLI", the selection rule is "FSMW", the pickup rule is "SMLT" and the dispatching rule is "SURO".

Table 1. Distribution function of the system servers and other specifications.

Server type	Distribution function
MTTF for GCs (10 units)	Normal (2402, 188) in hours
MTTF for GCs (10 units)	NegExp (8) in hours
Speed of inbound (15 units)	60 km/h on average (fixed)
Speed of outbound trucks (15 units)	60 km/h on average (fixed)
Speed of internal lift trucks (40 units)	25 km/h on average (fixed)
MTTF for inbound/outbound trucks	Erlang (610, 4) in hours
MTTR for inbound/outbound trucks	Erlang (5,3) in hours
MTTF for lift trucks	Erlang (963, 4) in hours
MTTR for lift trucks	Erlang (14,5) in hours
MTTF for RTGCs	Normal (2205, 48) in hours
MTTF for RTGCs	Normal (7,1.8) in hours
Available buffer for arriving containers at berth	Zero (fixed)
Available buffer for containers at each dock	12 units (fixed)
Capacity of each inbound or outbound truck	6 containers (fixed)
Capacity of each lift truck	1 container (fixed)
All available paths for inbound/outbound/internal trucks	Bilateral (fixed)
Loading and unloading time at each dock by a RTGC	0.05 h (fixed)
Each operation by a lift truck	0.04 h (fixed)
Number of arriving containers at each ship	45% containing 450 units, 15% containing 380 units, 18% containing 320 units, and the rest containing 250 units

Table 2. The possible control rules concept at a CrD.

Levels	Delivery rules	Selection rules	Pickup rules	Dispatching rules
1	SQLI	FSID	SLWT	SQLO
2	SURI	FSOD	SMLT	SURO
3		FSMW		LLWT
4		FSLQ		LLLT

4.2. Simulation model

The data needed for creating the model was collected and analyzed through recorded documents available in the system, in 2011 and 2012. Therefore, the data related to the arrival of 1035 vessels into system including the arrival times, berthing times, operation times at GCs, the number of loaded and unloaded containers, labelling times at MY, loading times at outbound docks, and unloading time at inbound docks. To obtain the most appropriate distribution functions and carry out the statistical analysis, the data is examined by Easy Fit tool in the simulation software (ED V8.1). By analyzing the historical data, it was shown that the containers types and sizes follow an empirical distribution. Also, by analyzing the arrival time of all vessels to the port and using the chi-squared test (95% as significant level), the inter-arrival times of arriving vessels have an Erlang distribution with the average of 8.25 hours and $k = 4$. According to the data gathered in actual operations, the number of movements for each GC follows the normal distribution with the average of 21 moves/hour and the standard deviation of 5.56. On the other hand, the service time of a GC has lognormal (180.83, 49.86) distribution in the real world which was used in the simulation model. The rest of the information is listed in Table 1.

5. Optimization via simulation

In this section, a hybrid meta-heuristic algorithm was developed based on Genetic Algorithm (GA) and the simulation technique. According to the system information, a dock has a cost of USD 8,200, annually, including the wages, repairs, and the depreciation of RTGC. This cost is USD 5,800 for a lift truck, and for an inbound/outbound truck is USD 11,800. Also, the port manager has set a penalty of USD 1.85 for each hour of lateness of a load when it is delivered to the customer (the yard at this study). According to the current information, the due date of a load has a uniform function between 12 to 36 hours with integer values which were coded in the simulation software. Therefore, the objective/Fitness Function (FF) is the summation of all these costs in a year knowing the value of the decision variables with their functional (operational and financial) lower and upper bounds such as internal fleets size ($40 \leq x_1 \leq 60$), the inbound

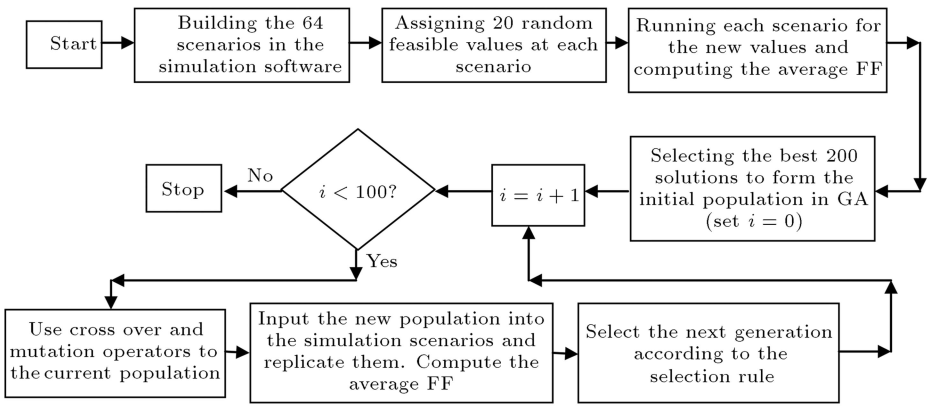

Figure 3. The flowchart of algorithm.

fleet size ($15 \leq x_2 \leq 25$), the outbound fleet size ($15 \leq x_3 \leq 25$) and the control strategies including the delivery rules ($1 \leq x_4 \leq 2$ and Integer), selection rules ($1 \leq x_5 \leq 4$ and Integer), the pickup rules ($1 \leq x_6 \leq 2$ and Integer), and the dispatching rules ($1 \leq x_7 \leq 4$ and Integer). The chromosomes structure is as the same decision variable definitions, i.e. it is an array of 7 elements. The population size is set to 30 individuals. The initial population was taken from 1280 randomly produced simulated solutions. First of all, 64 simulation models were built in the simulation software based on 64 different control rules. The value of x_1, x_2, and x_3 were coded in each model that could be set by the user. In each model, 20 random feasible values were assigned to x_1, x_2, and x_3, and the FF was calculated. Among the 1280 solutions, the first best 200 solutions were selected to form the initial population for the GA algorithm (according to the tuning process). The idea could help GA to be terminated more quickly. The termination rule was set to maximum 100 iterations in the GA. A key element of a GA is the selection operator which is used to select chromosomes (parents) for mating in order to generate new chromosomes (offspring). The selection operator was set to roulette wheel selection which parent chromosomes are probabilistically selected based on their fitness functions, the higher probability usually chosen for mating. The crossover operator of GA is a single point crossover. Offspring 1 inherits the first 3 genes from parent 1, and offspring 2 inherits the rest of genes. Also, the same process will happen for genes of parent 2 which will be inherited by the offsprings 1 and 2. In this way, the next population has feasible values, too. The goal of a mutation operator is to make infrequent changes on solutions at each iteration and consequently to avoid convergence to a local optimum and to diversify the population. In any chromosome, there are 7 genes. According to the gene feasible values, there are four possible sets such as A={Gene1}, B={Gene2, Gene 3}, D={Gene4, Gene 6}, and E={Gene5, Gene7}. First of all, two classes are selected randomly for mutation. If set A is selected, a random integer value between 40 and 60 is assigned to the first new gene of mutated chromosome. If set B or D or E is selected, the value of the gene will be swapped with the other member of the set. However, to have better results, the best chromosome in each generation is kept for the next generation. To tune the parameters, including population size (N_{pop}), the crossover probability (P_c), and the mutation probability (P_m) in GA, a Taguchi experiment was designed. The optimum values for the parameters were 200 for N_{pop}, 0.85 for P_c, and 0.05 for P_m. Every time that the GA needs to calculate the FF for a given chromosome, according to 4th, 5th, 6th and 7th genes, the related simulation model is selected and the simulation software replicates the model 35 times and gives the average value for FF to the GA. The explained procedure is an efficient way to have benefits both from the stochastic nature of the simulation model and the power of a GA to produce good solutions. Figure 3 depicts the proposed algorithm flowchart.

It must be noticed that since all variables do not follow the negative exponential distribution, the mathematical structure cannot be written explicitly similar to the ones which are usually used in queuing theory. Because we have not the memoryless property for the inter-arrival times of trucks and also for internal processing times, the fitness function cannot be written mathematically. Therefore, it is the simulation model which not only models the problem but also evaluates the average of the fitness function whenever the user puts new values for the decision variables into the simulation software. When the user sets new values for the decision variables, the simulation model is being replicated. Since there are several stochastic parameters in the model, it may result in different FF values even with a fixed value for the decision variables.

6. Computational results

Enterprise Dynamics V8.1 software and its programming language - 4DScript- have been used for designing all simulation models, Matlab software Version 2012 to code the GA steps, Minitab 16 for statistical tests, and Microsoft Visual Basic 2010 as the coordinator between the simulation software and Matlab software. All computations were run on a PC with a Core i6, 2.65 GHz CPU and 4GB of RAM. Figure 3 depicts the convergence trend of the proposed algorithm as the algorithm proceeds and the FF decreases and converging when the iterations approach 100. Also the FF is converging to USD 1,073,000 as the optimum value of the objective function. In 2012, just the penalties paid to arriving ships were USD 1.01 m plus the wages, depreciations and repair costs, and the total cost was USD 1.63 m. Therefore, the algorithm could reduce the total costs by 34.4%. The computational time was only 492 minutes - by evaluating the FF by 19345 times - which was worthy. It took only about 8 hours to reduce the annual costs by around USD 600,000. On the other hand, the best value for internal fleet size is 58 lift trucks, for the inbound trucks fleet size is 22 trucks, and for outbound trucks is 16 units. These results unveil another fact in the system. The penalty weight is very larger than the other costs in the system cost break down. The majority of penalties comes from the waiting time of the arriving ships. Therefore, the decision variables which are related to arriving loads have higher priority than the other variables. In this case, the increase in inbound fleet size is larger than the outbound fleet size. However, in the simulation experiments, the average utilization rate of GCs was 62%, it means that the GCs were not the bottle neck of the system and that is why it was not optimized during the investigations. Concerning the control rules, the optimum rule is "1324". On this basis, the optimum value for the "delivery rules" is SQLI, i.e. the best strategy for assigning, and incoming truck is the assignment of it to the dock with smallest queue length. Regarding the "selection rules", the best strategy is FSMW, and for "pickup rules," the best one is SMLT, i.e. the internal lift trucks must serve the loads with higher lateness time, first. Finally, LLLT is the best strategy for "dispatching rules." Again, the cost structure obliges the model to have more focus on lateness quantity. In order to have robust solutions, some sensitivity tests were carried out on the model. The control strategies were fixed to "1324," but the value of FF was depicted against x_1, x_2, and x_3. Figure 4 depicts the convergence trend of the algorithm. As an example, Figure 5 shows the FF against the internal fleet size. As the results show, when the value of the related fleet size increases, the FF decreases until its optimal value. After reaching the optimal point, any increase in the fleet size has almost no effect on the FF (except a small amount due to the running costs of adding a new fleet). The results are listed in Table 3.

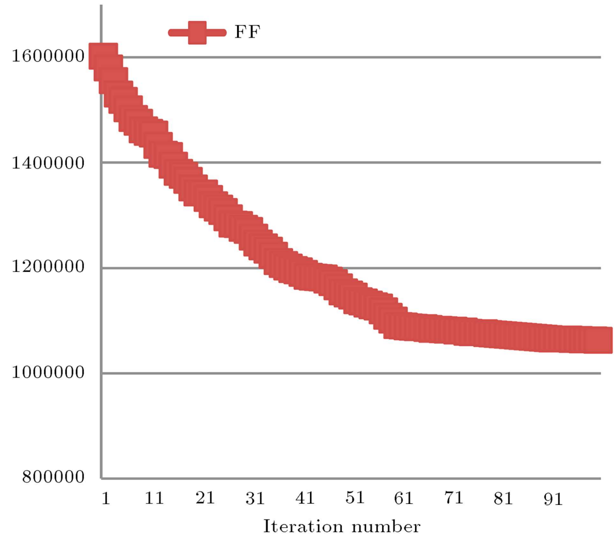

Figure 4. The converging trend of the algorithm.

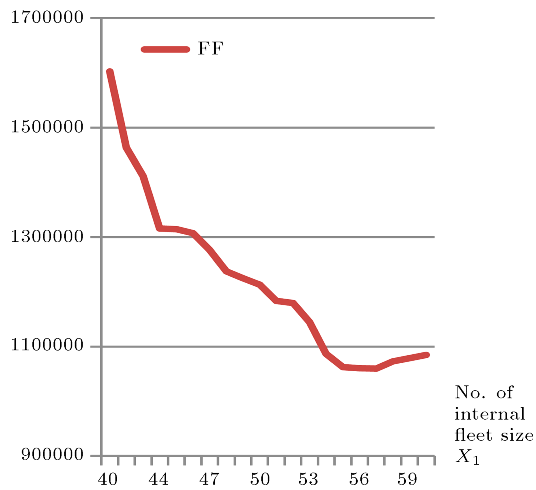

Figure 5. The FF trend against x_1.

7. Conclusions

In this research, a new general concept named "on-line CrD" was developed and tested in a real world

Table 3. Computational results.

Best FF	% Reduction in total annual costs	Computation speed	Best internal fleet size	Best in-bound fleet size	Best out-bound fleet size	Opt. control rule
USD 1.073.000	34.4%	492 min.	58 units	22 units	16 units	1324

case, at a container port. The study has two main contributions. The first is to introduce the on-line concept in cross-docking literature which is much more realistic in comparison to traditional model where all major events are supposed to be deterministic. In an on-line docking concept, all events are supposed to be stochastic characters and so a set of new decision variables were introduced. The second develops the CrD concept in a container port which could reveal other good applications of the concept. An OVS algorithm based on simulation technique and GA was developed to optimize the annual total costs at the port by tuning some integer decision variables such as internal, inbound and outbound fleet sizes, and the control rules. The problem was solved by the algorithm and the optimal values were found. Regarding the research restrictions, the author had some difficulties in data gathering step, because some kind of data had not been stored in the port database and it was necessary to take direct sampling with some limitations in human resource. Also, only the marshalling yard of the port was modelled and analyzed in this research, not the whole system. For future studies, it is recommended to develop the on-line CrD concept in the whole port or even other applications such as post offices, retail distributors, commercial rail way stations, etc. Also, it is highly recommended to model the problem using a multi-objective concept to achieve more than one goal at a time. On the other hand, the proposed solving algorithm could be improved in next studies by implementing better methods. In the proposed algorithm, for each evaluation of FF, the algorithm replicates the simulation model 10 times. Using a regressions function instead of using the simulation replications, the computational time can be decreased. Other heuristic methods such as Dynamic Multi-swarm Particle Swarm Optimizer (DMS-PSO), The Covariance Matrix Adaptation Evolution Strategy (CMA-ES), and the Self-adaptive Differential Evolution Algorithm (SEDE) are also recommended.

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Biography

Parham Azimi was born in 1974. He received his BS degree in Industrial Engineering from Sharif University of Technology, in 1996, his MS and PhD degrees in Industrial Engineering from Sharif University of Technology, in 1998 and 2005, respectively. Currently, he is the Assistant Professor of Industrial Engineering at Islamic Azad University (Qazvin Branch). His research interests include optimization via simulation techniques, facility layout problems, location-allocation problems, graph theory and data mining techniques.