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PREDICTION OF THE CONTAINER TRAFFIC IN A SEAPORT STOCKYARD USING GENETIC ALGORITHM.

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ABSTRACT

Usage of container for marine transportation is a practical and safe method of transferring goods turned to be one of the most important marine transportation mode in the recent years. The container terminals are among the important seaport facilities serving as a spot for the of the transport mode. In this way, containers are transferred between the trucks, trains or ships. Knowing the actual amount of containers in a storage area of a seaport is vital for planning and management issues. Especially for short term seaport management, one-day-a-head prediction of the container amounts in the storage area is necessary for taking precautions of the container traffic. In this study, a simple regressive model was proposed to predict the amount of containers in a seaport in a specific day by regressing the past records of incoming and outgoing containers. The model parameters were optimized using the genetic algorithm which is an efficient multi-parameter optimization technique. The results indicated that the model performance is sufficient for predicting the contain amount in a seaport considering the observed records of the past days.

Keywords: Genetic Algorithm., Container Traffic, marine transportation, seaport facilities

INTRODUCTION

Controlling container traffic in a seaport is important for an economic and reliable management. Especially the traffic forecasting is a beneficial tool for optimizing the container traffic by scheduling the assigned vehicles to a storage area. In this manner, knowing the amount of containers in a seaport storage area will lead the port authority to estimate the required number of trucks or train cars to be attained for the next days. For the traffic estimation purposes, regression techniques can be implemented. Also the implementation of soft computing techniques such as neural networks and several optimization algorithms for determining the model parameters are used. There exist many studies involving the implementation of genetic algorithm (GA) for seaports. Preston and Kozan (2001) proposed a container location model to minimize the turn around time of container ships, and solved using genetic algorithm (GA). This study models the seaport system with the objective of determining the optimal storage strategy for various container-handling schedules. (Kozan and Preston (2007) modeled the seaport system with the objective of determining the optimal storage strategy and container-handling schedule. It presents an iterative search algorithm that integrates a container-transfer model with a container-location model in a cyclic fashion to determine both optimal locations and corresponding handling schedule. A genetic algorithm, tabu search (TS) and tabu search/genetic algorithm hybrid are used to solve the problem. Vickson and Fujimoto (1996) examined the problem of optimal product location in a single bi-directional carousel storage and retrieval system Skinner et al. (2013) proposed a genetic algorithm (GA) based optimization approach to improve container handling operations at the Patrick AutoStrad container terminal located in Brisbane Australia. Study concreated on scheduling for container transfers and encode the problem using a two-part chromosome approach which is then solved using a modified genetic algorithm. Lau and Zhao (2008) implemented a mixed-integer programming model, which considers various constraints related to the integrated operations between different types of handling equipment in a seaport. Homayouni et al. (2009) proposed a heuristic algorithm to schedule the AGVs concurrently with quay cranes. A genetic algorithm is proposed to optimize the simultaneous scheduling of Automated guided vehicles in terminals. The results showed that proposed genetic algorithm can be used in practical implications while its running time is reasonably low.

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Genetic Algorithms

Genetic algorithm (GA) is a innovative way of solving the constrained or unconstrained optimization problems implementing biological selection similar to the nature (Whitley, 1994). The algorithm tried to alter the population for individual solutions in a repeatedly way. For each recursive step, the algorithm randomly chooses the samples from the population and categorize them as parents for producing the next generation of genes. After creating successive generations, evolution of the population is concluded for the optimal solution. The genetic algorithm if differentiated from the classical and derivative optimization algorithms in a couple of points. The standard algorithm creates a single point for each successive iteration and the sequence of points approaches to the most feasible solution. However, the GA creates a population of points for each single iteration cycle and the best point in the population converges to the optimal solution (Ahn, 2006).

Individual populations are considered in the search space for the GA such that each of them represent a possible solution for the considered problem. Every individual is considered as a finite-length vector or variables and suitable alphabet like binary is implemented. To continue the genetic analogy these individuals are likened to chromosomes and the variables are analogous to genes. Thus a chromosome (solution) is composed of several genes (variables). A fitness score is assigned to each solution representing the abilities of an individual to `compete'. The individual with the optimal (or generally near optimal) fitness score is sought. The GA aims to use selective `breeding' of the solutions to produce `offspring' better than the parents by combining information from the chromosomes. The simplest form of genetic algorithm involves three types of operators: selection, crossover (single point),and mutation (Melanie, 1996).

Selection: This operator selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to be selected to reproduce.
Crossover: This operator randomly chooses a locus and exchanges the subsequences before and after that locus between two chromosomes to create two offspring. For example, the strings 10000100 and 11111111 could be crossed over after the third locus in each to produce the two offspring 10011111 and 11100100. The crossover operator roughly mimics biological recombination between two single−chromosome (haploid) organisms (Melanie, 1996).

Mutation: This operator randomly flips some of the bits in a chromosome. For example, the string 00000100 might be mutated in its second position to yield 01000100. Mutation can occur at each bit position in a string with some probability, usually very small (e.g., 0.001) (Melanie, 1996).

In the modelling progress, the input and output container records were obtained and evaluated. For this purpose a past study of (Canivar, 2003) was used. The considered storage area has three input sources from sea, railroad and trucks. Due to the reason of the train transportation is not significant among the other transportation modes (approximately less than <0.4%), the containers transported from this mode was neglected. Additional data gathered from the port authorities according to a two year recording period monthly observations of the current container numbers in the stock area. The introduced model basically assumes that a single container is no longer stay at the stock area more than four days. The proposed model is type of a regression model based on the past records of differentiation (net loads in TEU) between the incoming and outgoing container for various sources is shown in mathematical form as Eq.1.

$$ST = \sum_{i=1}^{4} X_1(i)K_t(i) + \sum_{i=1}^{4} X_2(i)G_t(i) + \sum_{i=1}^{4} X_3(i)Z_t(i) \quad (1)$$

In the equation above, ST represents the current amount of containers in the storage area for a specific day. X_1,X_2 and X_3 are the coefficients of the net container movements correlating the container amount of the present day with the historical records In the modelling phase, the X_1 X_2 and X_3 vectors are constituted as the parameters to be optimized in the genetic algorithm. The K G and Z indices are defined as the net amount of containers added or taken from the stock area by truck (K) by (ship) and by train (Z). Also "i" is a symbol defining the lag as if i=1 than it indicates the same day and i=2 is the previous day. In this instance K(3) represents the amount of containers

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added or subtracted from the stock yard space two days ago.

ANALYSIS & DISCUSSION

İzmir seaport, Operated by Turkish General Directorate of State Railways (TCDD), is a vital export position in western Anatolia of Turkey (WFB, 2015). The İzmir city is the third largest city of Turkey with a population over 4 million of inhabitants is an economically important city with its exports corresponded to 6% and its imports 4% of Turkey's foreign trade (TEA, 2014). The seaport is connected to the railway and highway networks. İzmir seaport is a suitable node for import and export due to its strategic location. Plan and aerial views of the İzmir seaport are shown in Figure 1. The daily arriving and departing containers rate in TEU is shown in Figure 2 and Figure 3.

Figure 1. *(a) Plan and (a) aerial views of the İzmir seaport. (Retrieved from Bookyourtransfer.com)*

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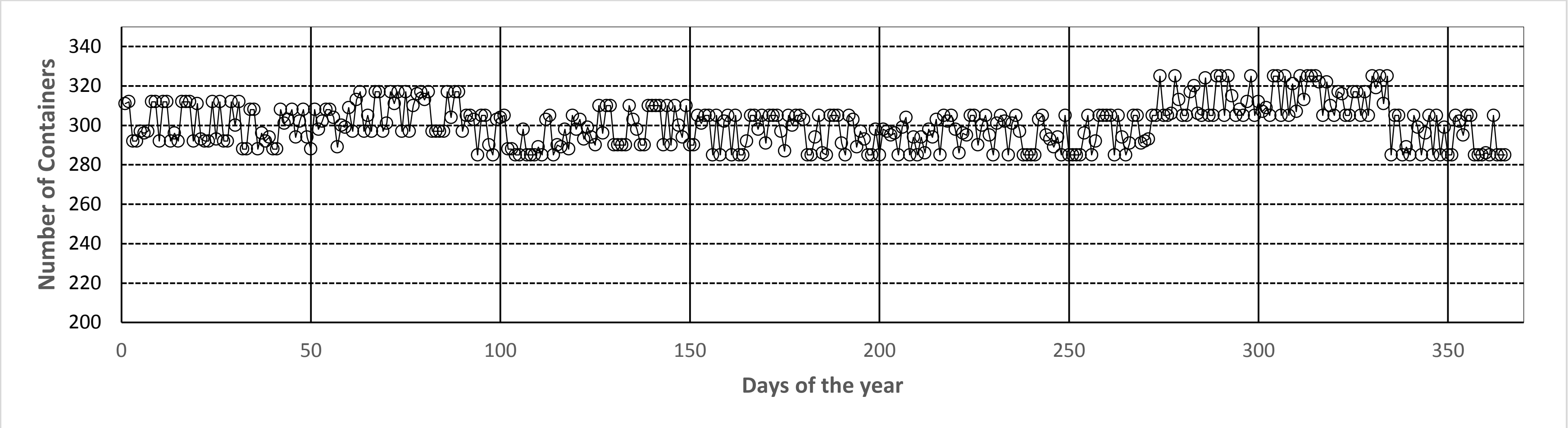

Figure 2. *Daily arriving containers with trucks in TEU*

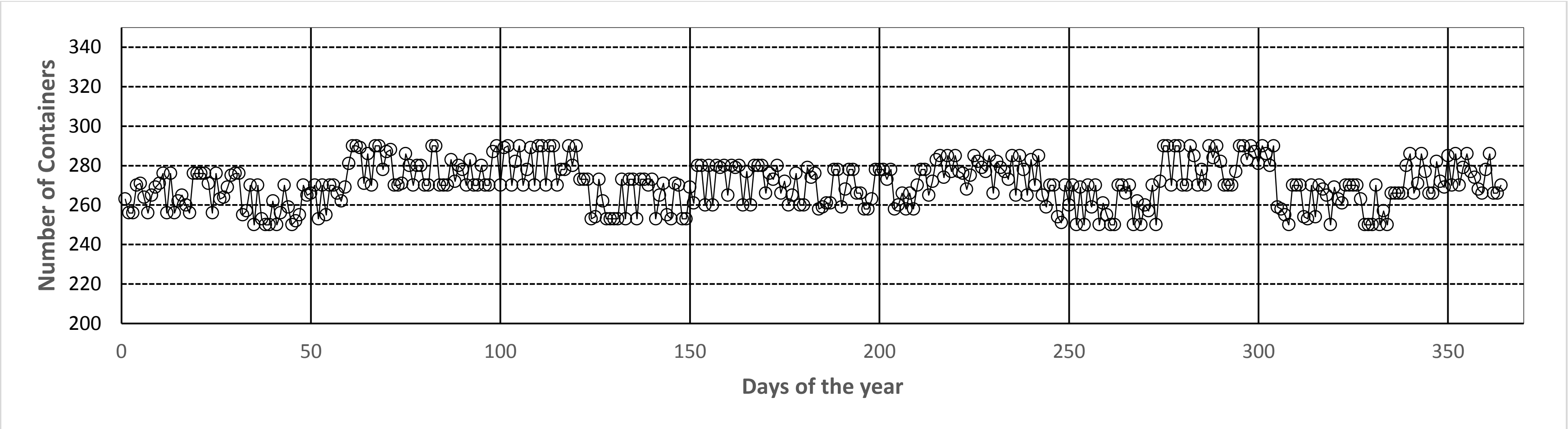

Figure 3. *Daily departing containers with trucks in TEU*

In the genetic algorithm, several parameters were used as shown in Table 1 below. In the modelling phase Matlab genetic algorithm module was used (Chipperfield & Fleming, 1995).

Table 1. *Parameters of the genetic algorithm*

Parameters of Genetic Algorithm	Values
Number of variables	12
Population size	10
Creating function	Uniform
Scaling function	Rank
Selection function	Roulette
Elite count	2
Crossover fraction	0,8
Mutation function	Gaussian
Crossover function	Scattered
Stopping criteria	Maximum 100 generations

The calculated and observed containers in the storage area is shown in Figure 4 below in monthly basis.

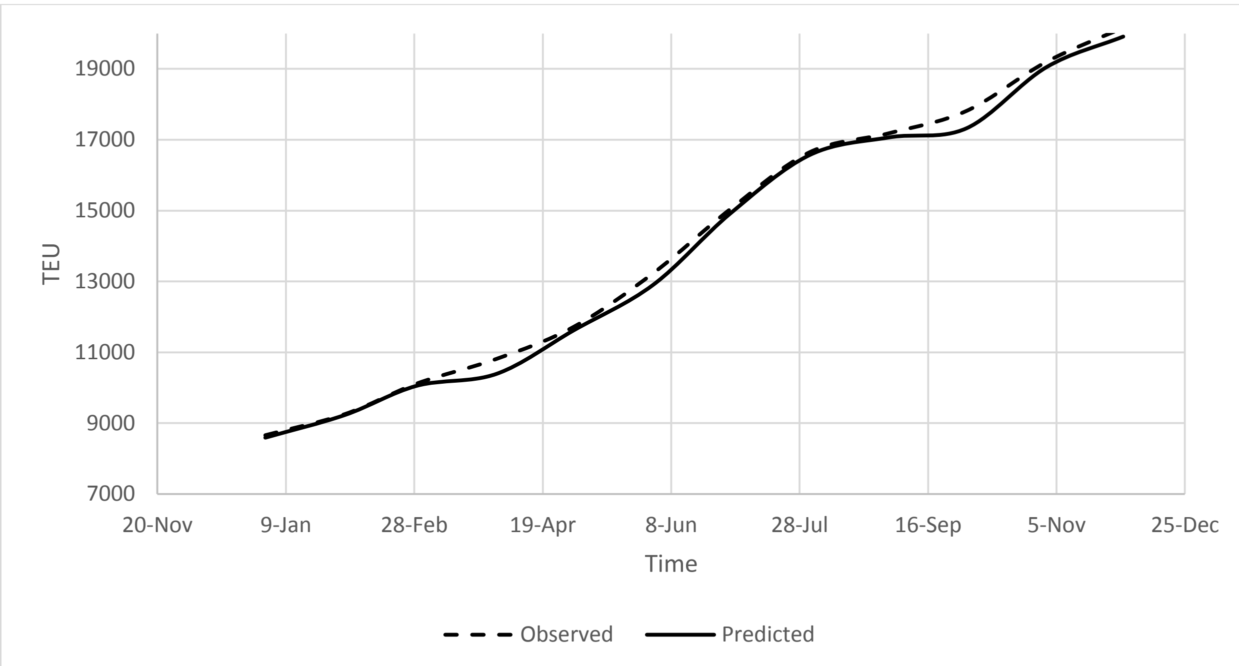

Figure 4. *Calculated and predicted container amounts in the storage area in monthly basis.*

The model parameters optimized for each month is shown in the Table 2. The table also includes the fitness function. By comparing the observed and predicted values for all months and for each single month it is concluded that model results represents a well suit with the real data.

Table 2. *Parameters of the regressed model optimized by genetic algorithm.*

MONTHS	X(1)	X(2)	X(3)	X(4)	X(5)	X(6)	X(7)	X(8)	X(9)	X(10)	X(11)	X(12)	FitFNC
Jan	1,25645	0,37444	-0,20648	0,01602	-0,96537	0,70975	-0,70673	2,14463	2,0982	2,34832	2,34832	2,55093	-0,03667
Feb	0,39006	0,44283	0,80786	0,51717	2,45221	0,61411	-0,545	2,9127	1,45904	2,54026	3,04625	1,29749	-0.04013
Mar	1,38714	1,92958	0,00457	1,43437	-0,25889	6,29416	2,94556	-4,34353	5,45008	2,97747	2,1834	0,58055	-0.02661
Apr	0,50004	0,63962	-0,03407	0,04883	2,00748	-1,48694	2,48007	1,32777	8,13522	0,07833	8,75774	11,9101	-0.01742
May	-0,1052	-0,45552	-0,04239	-0,75371	4,91983	2,97344	0,40638	1,09956	5,62159	4,24389	1,2791	3,03463	-0.02904
June	1,31853	1,23755	1,54099	0,63992	-3,68198	-3,00805	-1,96517	-4,8885	5,64979	5,10184	3,34689	4,97461	-0,01421
July	1,3843	-0,24882	0,50396	0,81208	0,12865	3,50318	-0,66671	2,15142	3,10581	4,88176	3,88337	3,90039	-0,02273
Agu	2,94022	2,63381	2,30661	2,56063	-1,63799	-3,56268	-0,89021	-0,18562	2,72665	3,6969	4,91197	2,89588	-0,02710
Sep	1,31421	2,0235	1,09853	2,67444	0,44195	-0,37406	-2,21129	1,64409	6,96482	-0,23724	5,13755	6,05011	-0,02342
Oct	1,02397	2,11006	1,85917	3,11632	4,13384	0,57218	4,11129	-0,19672	8,36924	7,27241	6,22293	4,21177	-0,01527
Nov	1,94423	2,22785	0,71579	0,48435	3,96412	-2,56164	0,95617	1,10984	7,1661	5,82177	6,47754	3,63678	-0,01584
Dec	0,80949	0,7322	0,60994	0,19666	0,78446	1,38646	3,46796	-1,9088	7,36953	7,52953	6,00465	8,77865	-0,01301

CONCLUSIONS

Comparing with the observed data, the model proposed for predicting a-day-ahead container amount by regressing the past records of container traffic is found to be reasonable. The comparisons were made considering the real container traffic records of 2002 in İzmir seaport. Model results also indicated relatively larger deviations comparing with the monthly averages. The proposed model also can be used for performing a simulation of the stock area for the caser of high traffic and the maximum amount of containers probable to be observed in the stock area was found as 19913 TEU. This is also a reasonable prediction comparing with the real observed amount of 20165 TEU. The deviations between the calculated and observed values can be described by the fact that, there exist many model parameters. A future study can be performed considering the parameter alteration of the genetic algorithm.

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