



A Decision Support System for Multi-Objective Porcelain Container Loading Problem Based on Genetic Algorithm

*¹Durmuş Özdemir, ²Derya Deliktaş, ³Elif Güler Ermutaf

¹Kütahya Dumlupınar University, Department of Computer Engineering, Kütahya, Turkey durmus.ozdemir@dpu.edu.tr, 

²Kütahya Dumlupınar University, Department of Industrial Engineering, Kütahya, Turkey derya.deliktas@dpu.edu.tr, 

³Kütahya Porcelain Industry and Commerce Incorporated, Kütahya, Turkey germutaf@gmail.com, 

Abstract

The multi-objective genetic algorithm approach for solving the Porcelain Container Loading Problem (PCLP) has a vital role in the global logistics industry. In this paper, a logistical problem with one constrained container loading problem that has to be filled with a set of boxes has been the focus. This study addresses a real-life problem that exports departments in the international porcelain industry face. Our objective is to maximize product profitability and delivery priority. Since the CLP is known as an NP-hard problem, the Genetic Algorithm (GA) approach is proposed to solve the problem based on these objective functions. The parameters of the GA affect the obtained results. We made tuning by using an experimental design in order to determine the appropriate parameters. The main contribution of the study is to present a new decision support system taking into account the objectives of the delivery time and profit rate priority of the manufacturer in the porcelain sector. Thus, loading according to the company's priority and distribution in the shortest distance has been successfully achieved. The results show the efficiency of the proposed decision support system, which solves the CLP with up to 12 different products in boxes of different volumes.

Keywords: Decision support system for porcelain industry, container loading problem, experimental design, multi-objective problem.

1. INTRODUCTION

In a competitive worldwide market, studies regarding the decision support system offering solutions and suggestions for Container Loading Problem (CLP) and Routing Problem (RP) in industrial and commercial decision-making processes are pretty critical [1]. The goal of the CLP is to put a set of orthogonal boxes to a limited capacity area called containers [2]. Containers are delivered with the optimal routes from depots to several cities or customers by considering some constraints [3]. When the literature is examined, CLPs are classified into two main groups [4, 5]. Studies in the first group are based on the minimization problem, where the storage space is sufficient to load all the boxes. The objective function is to minimize the number of containers required to load all available boxes. In the studies of the second group, the issue is the problem of output maximization. It is not possible to load all the boxes for a limited volume of container area. Therefore, the goal is to choose a box subset that maximizes the volume or value associated with the load.

The CLP is a type of knapsack problem formulated as considering limited container capacity, being one of the fundamental problems in combinatorial optimization and

CLP is classified under the category of NP-hard problem [6-8]. It has crucially significant applications in the packaging and transportation industries. This study focuses on road transportation in the porcelain industry, mainly consisting of single container loading. For loading, a set of rectangular boxes of known dimensions is used in a limited container. This paper presents a decision support system based on the multi-objective genetic algorithm (GA) approach to assist decision-makers in generating an optimized solution for the Porcelain Container Loading Problem (PCLP). The objective of the proposed approach is to maximize the profit of the product loaded and the priority of delivery to enhance customer satisfaction.

As a result of this study, a decision support system based on the multi-objective GA approach for solving the CLP was developed for manufacturers in the porcelain sector, taking into account the priority of delivery time and profit rate. Loading according to the company's priority and distribution in the shortest distance has been successfully achieved. Sensitivity analysis was performed considering the different objective weights of each objective. Thus, it is ensured to perform the loading process with a container occupancy rate of 98.19% for the appropriate weight combination of the objectives. After loading the container, the container was

* Corresponding Author

routed considering the shortest distance among all distribution centers.

The paper is organized as follows: Section-2 provides a brief overview of PLCP-related work for the loading and routing process. Section-3 presents an overall definition of the problem. In Section-4, the problem is defined by applying a bi-objective mathematical model. In Section-5, a MOGA-based approach is proposed. Section-6 indicates the proposed DSS with an example based on a real-life problem in the porcelain industry. Section-7 presents sensitivity analysis performed by considering the different weights of objective functions. Finally, Section-8 provides the conclusion and suggestions for the future.

2. CONTAINER LOADING PROBLEM

Container loading contains the cutting and packing problem, which is an NP-hard problem. Wäscher et al. [5] proposed the typology for cutting and packing problems, classifying the problems according to dimensionality, the assortment of large or small items, the kind of assignment and the shape of small items [12]. Whether the assortment is strongly heterogeneous (many species) or weak heterogeneous (several species) is usually related to the variety and number of large and small items. The studies on assignment problems in the literature focus on two main objectives. The first group of studies, the number of containers not being enough to cover the entire load, aims to increase the number of loads to the maximum level, while the second group of studies aims to minimize the cost of containers when there are enough containers [12-14]. Bortfeldt and Wäscher [15] suggested a classification of container loading problems for real-world constraints. They mention distinctions between: container-related constraints (weight limits, weight distribution); item-related constraints (loading priorities, orientation, stacking); cargo-related constraints (complete shipments, allocation); positioning constraints; and load-related constraints (stability, complexity). The solution suggestions for container loading problems are to place the dimensions of n boxes with height, length and width information in a certain container. Following the settlement comes the objective to minimize the space in the container and maximize the container volume [16]. Zhao et al. [17] examined the container loading problems in 14 different sub-categories, depending on the type of container and cargo, yet it was stated that the main purpose was to fill the container as fully as possible according to the constraints.

Decision support systems (DSSs) assist decision-makers in decision-making processes related to the problems that may be rapidly changing and not easily specified in advance result reporting, operation management, process evaluation, etc. Especially in the last decade, DSS has been preferred because it has made the decision-making process more manageable. Thus, the design of the DSS interface is crucial for decision-makers. Many container loading studies are based on decision support systems in the literature [18-24].

The algorithm in the DSS is mainly based on mathematical modelling and metaheuristic methods. The framework of

DSS is constructed considering objective functions and constraints in mathematical modelling. In CPL, a mathematical model has also been developed for container capacity utilization and departure times of loaded vehicles [25].

In this study, a user-friendly DSS based on a multi-objective Genetic Algorithm (GA) approach was proposed in the search for a solution to the capacity management problem in the container terminal, aiming at presenting a better service level to the customers in the porcelain sector. This DSS based on metaheuristic algorithm considers two objective functions: simultaneously maximizing product profitability and delivery priority. There are many studies about the container loading problem during the past decade, as shown in Table 1. It has been limited research, including both multi-objective function and DSS. To the best of our knowledge, such a case study applied to the porcelain sector has not been done before. It is thought that DSS will contribute to container loading problems, particularly in the porcelain sector.

Although the CLP has widely been studied in the literature as seen in Table 1, there is not any investigation on a study applied to the porcelain sector as it is done in this study. Production priorities in the porcelain industry are constantly changing due to profitability, customer satisfaction and storage constraints. Depending on these situations, the order of shipment transactions varies. For this reason, there is a need for decision support systems for container loading operations, and solution proposals containing decision support systems should be optimized with artificial intelligence-based algorithms. With the use of the container loading and vehicle routing software suggested in our study, it is predicted that time savings, ease of inspection, effective planning and profitability will increase in the loading and delivery processes in the porcelain sector and other sectors.

3. PROBLEM DEFINITION

In this study, a decision support system is proposed for the problems of loading and shipping goods for "Kütahya Porselen Industry Incorporated", one of the world's largest porcelain manufacturers. The company presents both modern and exclusive designs to its consumers in the international arena. There are kitchenware products such as dinner sets, cup sets, bowls, mug sets, etc. Special decorative porcelain products such as handmade vases, paintings, etc. based on customer demands. However, unique decorative porcelain products are shipped to the customer using special cargo companies instead of containers and boxes with different volumes. These boxes are placed on pallets in the packing department. The pallets are lifted via a forklift and placed in the container. As seen in Figure 1, in the porcelain industry (01), products (02) that will be delivered are sent to the storage area (04) after the packing process (03). The loading (06), considering the delivery time (05) of the products, are routed (08) by taking into account the shortest route between the depots to be distributed (07).

Table 1. The summary of the related research

Ref.	Scope of the Research	Solution Method	Number of Objective Functions			DSS
			Single	Bi	Multi	
[3]	Air cargo operations	Literature Review				
[4]	Integrating pricing and capacity decisions in car rental	MM		√		√
[5]	Automating the planning of container loading for Atlas Copco	GA		√		√
[6]	Logistics Problems in Smart-City Environments	Unbalanced version of the Hungarian algorithm & Hybrid GA	√			√
[7]	A capacity management problem at a container terminal	Tabu Search Algorithm	√			√
[8]	The stowage of maritime containers in inland shipping	MM & Hybrid VNS and Greedy Search	√			√
[9]	Integrated container handling in a transshipment hub	Queuing model & Simulation			√	√
[9]	The air cargo load planning problem	Literature Review				
[10]	Internal and external transportation	MM & GA	√			
[11]	Container Stacking Problem	A GRASP-based metaheuristic		√		√
[12]	Container Stacking Problem	Reward-based Stacking Algorithm			√	
[13]	Intelligent agent system for efficient logistics transport	Integrated NSGA-II & SA	√			
[14]	Cargo transportation by truck	Physics simulation tool & Multiple regression analysis	√			√
[15]	Priority-based container loading problem	Hybrid GA & FLC	√			
[16]	Planning the route of container ships	A fuzzy genetic approach			√	
[17]	3-D container loading problem	Biased random-key GA			√	
[18]	Output maximization container loading problem	Stochastic dynamic programming		√		

Abbreviations: DSS: Decision Support System, MM: Mathematical Model, VNS: Variable Neighborhood Search, FLC: Fuzzy logic controller, NSGA-II: Non-dominated Genetic Algorithm II, SA: Simulated Annealing



Figure 1. Flowchart of container loading & routing in the porcelain industry

In this study, the container loading problem was studied by considering the container capacity constraint with two factors to be maximized simultaneously: the priority delivery date and the profitability of each product. The container capacity was set as the volume of the container. This volume is the 20ft container size in the company. For the objective function value calculation of the priority delivery date, products are ranked in ascending order according to the lead time of each product. Then, the coefficient value is assigned from a large value to small value. This calculation provides a high priority to products of which delivery due date is near or delayed. Thus, it is aimed to ensure customer satisfaction.

The other objective function is value computation, and it is required to load the products having high-profit margins per product. The weighted sum scalarization method was used to convert into a single objective. Since the weights of each objective function affect the obtained results, the sensitivity analysis was carried out based on the different weights of the objectives. Depending on the objectives and constraints, the routing is designed by considering the distances from the depot to the cities after the container is loaded. The following assumptions are taken into consideration.

- (1) Loading is made based on the volume of the boxes.
- (2) All the loads in the boxes are considered to be consisting of porcelain dinner sets (the items in the set can be packed separately).
- (3) The volumes of the pallets used for the calculations are neglected.

In this research, the operational decision support system software based on the multi-objective genetic algorithm approach was used to solve the container loading problem. The multi-objective GA approach based on DSS for PCLP system architecture is shown in Figure 2.

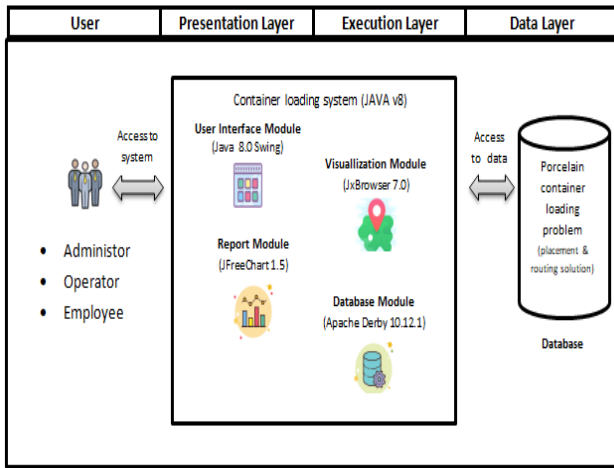


Figure 2. The multi-objective GA approach based on DSS for PCLP System Architecture

4. BI-OBJECTIVE MATHEMATICAL MODEL

Many studies propose mathematical programming, heuristic and metaheuristic approaches to solve container loading problems [27]. In this study, firstly, the problem is defined using a bi-objective mathematical model, and then, a multi-objective metaheuristic approach is presented for solving the PCLP.

The bi-objective mathematical model of the PCLP needs optimization of the priority delivery date and the profitability of each product simultaneously subject to the following constraints:

Indices:

i : Product index $i=1,2,\dots,n$

Parameters:

q_i : The profit rate of product i

t_i : The priority value of the product i by the delivery time

v : Volume of the container

Decision variables

x_i : The quantity of the product i loaded into the container

y_i : 1, if the product i is loaded into the container and 0 otherwise

$$Max \left\{ \sum_{i=1}^n q_i x_i y_i \right\} \text{ and} \tag{1}$$

$$Max \left\{ \sum_{i=1}^n t_i x_i y_i \right\} \tag{2}$$

Subject to:

$$\sum_{i=1}^n w_i x_i y_i \leq v \tag{3}$$

$$y_i \in \{0,1\} \ \& \ x_i \geq 0 \tag{4}$$

Eq. (1) maximizes the product profitability, while Eq. (2) maximizes a high-profit margin per product. Eq. (3) provides the container capacity constraint. Eq. (4) defines both positive

and binary variables. The objective functions are converted into a single objective through Eq. (5).

$$Max \left\{ w_1 \sum_{i=1}^n q_i x_i y_i + w_2 \sum_{i=1}^n t_i x_i y_i \right\} \tag{5}$$

Subject to:

Equations 3-4 are all satisfied.

w_1 and w_2 represent the significance weights of the objective function. $w_1+w_2=1$ and $w_1, w_2 \geq 0$ should be provided.

5. PROPOSED MULTI-OBJECTIVE GENETIC ALGORITHM

Traditional approaches solve multi-objective problems, including dynamic programming, random methodologies, and gradient approaches, whereas modern heuristic methods include cognitive paradigms such as artificial neural networks, simulated annealing, and Lagrange approaches. Some of these methods are used to find (approximately) optimal solutions, but convergence times can be longer than estimated. For this reason, the multi-objective GA approach is implemented based on the principles of natural biological evaluation, and (approximately) optimal solutions are obtained [30]. Since container loading problems are called NP-hard problems [6-8] in the literature, we proposed a metaheuristic algorithm to solve these problems. In our study, the genetic algorithm begins with the initial population, and then the fitness values are computed considering the maximization of product profitability and delivery time. After calculating the fitness values, the selection, crossover, and mutation operator are applied to each solution. The multi-objective genetic algorithm is run until the termination criteria are satisfied. Thus, the best solution is obtained at the end of the algorithm.

Algorithm 1 illustrates the solution of the multi-objective GA approach for the PCLP. The following sections depict the components of the multi-objective GA design in detail.

Algorithm 1 Pseudo-code of the proposed algorithm

```

Randomly generate an initial population
Compute the fitness of each individual
while termination criteria are not satisfied, do
    Choose parents from the population ← (population, tour size)
    Perform crossover to produce offspring ← (one-point crossover, parents)
    Perform mutations ← (bit-flip random, offspring)
    Calculate the fitness of each individual
    Replace the parents with the corresponding offspring in a new generation
end while
Return the best solution
    
```

5.1. Chromosome representation

In this section, a chromosome is designed to represent the solution to our problem. As a sample, a set of 12 different

products is used. The chromosome representation consists of five vectors ($v_i(t)$, $i=1, 2, \dots, 5$; $t=1, 2, \dots, 12$) as follows:

- (1) $v_1(t)$, whether the product is loaded in the t position,
- (2) $v_2(t)$, how many amounts the loaded product is in the t position,
- (3) $v_3(t)$, the volume of the box of the loaded product in the t position,
- (4) $v_4(t)$, the delivery priority of the loaded product in the t position,
- (5) $v_5(t)$, the profit of the loaded product in the t position.

v_1 consists of the 0 or 1 values and is randomly assigned to the t position. The value 1 means that the product is loaded and otherwise not loaded. In vector v_2 , the amount of that product is determined. For this calculation, a randomly generated value between at least half of that amount and the available amount of that product is used for each position. The available value is set as the demand value of the customers. The volume of each product set is defined in vector v_3 . A priority value is assigned a coefficient value according to the proximity of the delivery date in the vector v_4 . In this computation, products are ranked in ascending order according to the lead time of each product. Coefficient value is assigned to small value from large value. If two or more products have the same delivery date, the same priority value can be assigned (as seen in the 3rd and 11th positions in Figure 3).

In the case of products with delayed delivery, a value with the highest priority is assigned as a coefficient value. The vector v_5 shows the profit margin per product. The solution representation includes the vectors v_1 and v_2 , while the others are the supported data constructors. The chromosome representation containing these vectors is shown in Figure 3. As a sample, Figure 3 shows that the second product is loaded because a value in the second position is 1 in the vector v_1 . In the vector v_2 , 292 items are loaded from the second product. It is computed as 292×3000 cm³ because the volume of each of the second products is 3000cm³.

Position: t	1	2	3	4	5	6	7	8	9	10	11	12
$v_1(t)$	0	1	1	1	1	1	0	1	1	1	1	0
$v_2(t)$	199	292	96	106	461	1085	374	180	1579	838	1499	7
$v_3(t)$	1000	3000	250	4050	1520	1500	3500	4505	5000	3000	6700	7500
$v_4(t)$	1	5	8	9	7	10	2	6	3	4	8	11
$v_5(t)$	1	2	5	4	3	2	4	7	6	4	3	7

Figure 3. DSS based on the multi-objective GA approach for PCLP Architecture

5.2. Evaluation of fitness function

There are many studies on the performance of genetic algorithms and traditional methods in the literature. However, most of these do not include enough information

about the fitness function used by the genetic algorithm, whereas the fitness function affects the entire performance of the model [17]. The larger the fitness function value (for the maximization problems), the better the performance of the chromosome. After calculating the objective values for the priority delivery date and the profitability of each product, the weighted-sum scalarization method (WSM) is used to convert into a single objective. WSM proposed by Miettinen [18] is the most popular scalarization method for Pareto efficient solutions using Eq. (5).

Population initialization is vital for evolutionary algorithms as it can affect the speed of convergence and the quality of the result [19]. In this study, random population initialization is used to generate better solutions.

5.3. Genetic operators

Genetic operators are essential for the diversification of the population. Operators of mutation, elitism, selection, and crossover are adapted to provide a feasible solution to the research problem.

Crossover operator; the crossover operator enables generating better chromosomes through gene exchange. In the crossover example in Figure 4, the crossover point is randomly selected between 1 and the length of the chromosome l . In the two paired sequences, the sections after this cross-section are replaced, and two new offsprings are obtained.

Mutation operator; the main purpose of the mutation is to keep the population diverse. The bit-flip mutation operator is utilized to optimize functions over binary strings in this study. If the generated value between 0 and 1 is smaller than the mutation rate, the allele of the gene is changed from 0 to 1 or 1 to 0. This process is implemented for each gene between 1 and the length of the chromosome l .

Selection operator; employing a good selection operator ensures the probability of the survival of the best individuals. There are many standard selection operators in the literature, such as roulette wheel selection, rank-based selection, tournament selection, and seed selection. At this stage, tournament selection is used because of better convergence and computational complexity [20].

Elitism; this operator ascertains that the fittest chromosomes preserve from one generation to the following and guarantees that their characteristics cannot be lost after crossover and mutation operations [21].

5.4. Setting the parameters of the multi-objective GA

Since the multi-objective GA parameters impact the results, a full factorial experimental design is used to determine the appropriate parameters. Parameter tuning of a genetic algorithm can significantly affect the performance of the algorithm [31]. The steps for the application are presented as follows:

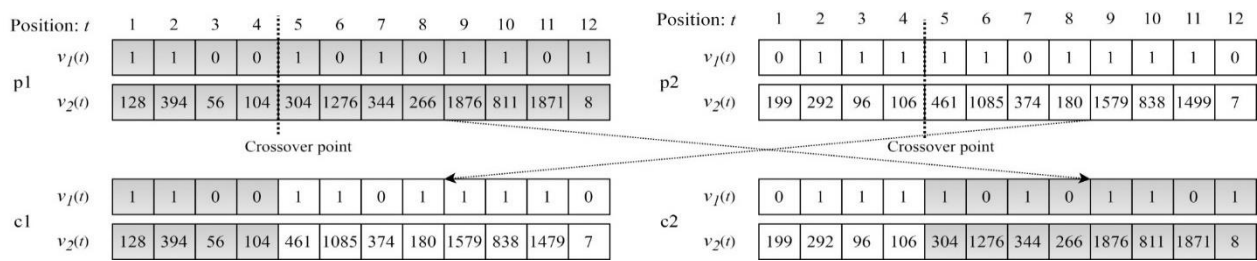


Figure 4. Chromosome representation of the proposed model

Step 1: Determination of the appropriate parameters in the multi-objective GA approach, 12 different product data were taken from the company's delivery process in the porcelain industry.

Step 2: Population size, crossover rate, mutation rate, and tournament size are selected as the main factor. Factors and levels are given in Table 2.

Table 2. Factors and levels for the multi-objective GA approach

Factors	Level 1	Level 2	Level 3
Population size	30	50	70
Crossover rate	0.6	0.8	1.0
Mutation rate	0.05	0.10	0.15
Tournament size	3	5	7

Step 3: To investigate the factors' effectiveness, 81 (3 × 3 × 3 × 3) different experiments were conducted. In addition, the result of each experiment is determined based on independently 31 runs to provide the accuracy of the solutions. Thus, the number of experiments required for this

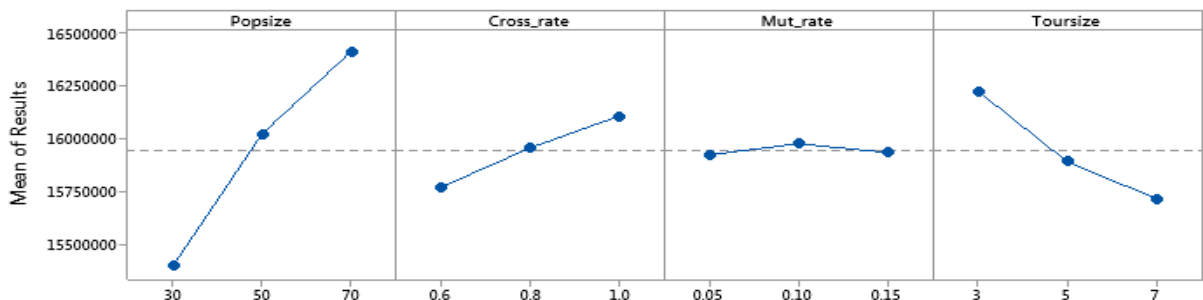


Figure 6. Main Effects Plot for w1=0.5, w2=0.

6. EVALUATION OF THE PROPOSED DECISION SUPPORT SYSTEM

The conceptual design and improvement of a Decision Support System (DSS) for the strategic design are essential for managing operative activities in a porcelain industry system. This section indicates the use of the proposed DSS via a real-life problem in the porcelain industry put forth here as an example. A two-stage DSS was suggested in this research. The container loading process is implemented using the multi-objective GA approach with suitable parameters in the first stage. Then, the container is routed to the determined cities. To illustrate how the DSS is used, the example of 12 different products is presented. Dealers mainly demand these products among product categories

produced in the porcelain factory. In this sample, the products are distributed to dealers in 10 different cities in different regions throughout Turkey. The steps for solving the problem in DSS software are as follows:

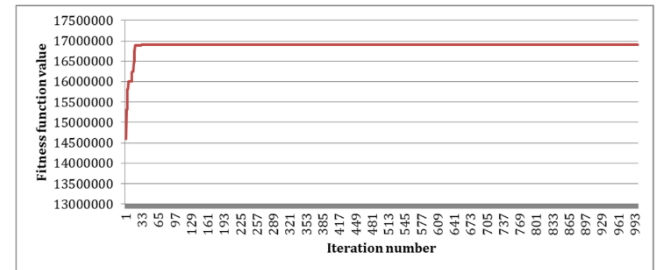


Figure 5. The graph of the convergence

Step 4: The variance analysis was performed by using Minitab 18 software. The main effect plot of this problem is shown in Figure 6. As a result of the variance analysis, Population size (Pop size), Crossover rate (Cross_rate), Mutation rate (Mut_rate), and Tournament size (Tour size) are obtained as 70, 1.0, 0.1, and 3, respectively. In this section, the weights of objective functions are considered as w1=0.5 and w2=0.5.

Step 1: In the first stage, the data belonging to each product, such as barcode number, material number, material name, delivery date, quantity, destination city, and depot, as shown in Figure 7, are entered.

Decision Support System Panel
Multi-objective Genetic Algorithm Approach in Porcelain Industry

Product Data Solve Calculate Delete Close Program

Barcode:

Barcode No	Material no	Material Name	Delivery date	Quantity	Destination City	Depot ?
8690053527616	AO18DU	16 cm Flat Plate	Wed Apr 15...	2400	Bursa	false
8690053527618	AO18DU	18 cm Flat Plate	Thu Apr 16 ...	4800	Kütahya	false
8690053527621	AO21DU	21 cm Flat Plate	Fri Apr 17 0...	1200	Bilecik	false
8690053527624	AO24DU	24 cm Flat Plate	Sat Apr 18 ...	1440	Eskişehir	false
8690053527627	AO27DU	27 cm Flat Plate	Sun Apr 19 ...	6000	Ankara	false
8690053527630	AO30DU	30 cm Flat Plate	Mon Apr 20...	7680	Antalya	false
8690053527622	AO22DU	22 cm Flat Plate	Tue Apr 21 ...	7920	Ankara	false
8690053527312	EO12KR	12 cm Bowl	22.Nis.2020	4080	Kütahya	false
8690053527314	EO14KR	14 cm Bowl	22.Nis.2020	22848	Kütahya	false
8690053527317	EO17KR	17 cm Bowl	22.Nis.2020	12492	Kütahya	false
8690053527320	EO20KR	20 cm Bowl	22.Nis.2020	12156	Kütahya	false
8690053527314	FO14KK	14 cm Joker	22.Nis.2020	12000	Kütahya	true

Figure 7. Data entry screen

Step 2: The list of destination cities is included in the combo box. The destination city of each product is selected from the combo box. Since it has to be one depot, it should be marked as one of the destination cities listed as a depot. Therefore, that city on the depot column is selected as true (see Figure 8).

Destination City	Depot ?
Bursa	false
Kütahya	false
Bilecik	false
Eskişehir	false
Ankara	false
Antalya	false
Ankara	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	false
Kütahya	true

Figure 8. Depot city selection

Step 3: As seen in Figure 9, all parameters of the genetic algorithm are entered.

Input Data

Genetic Algorithm Settings Parameters

Crossover Rate: 1.0 Tournament size: 3

Mutation Rate: 0.15 Population Size: 70

No of Generations: 1000 Weighted Sum Scalaration

Figure 9. Sensitivity analysis based on objective weights

Step 4: The type of container is determined among the related choices (see Figure 10).

Container Loading Settings

Container Type: 20" CONTAINER

Figure 10. Container loading setting

Step 5: In the container loading process, the weight data are processed in the relevant areas of the software. These values show the weights of objective functions: product profitability and delivery priority (see Figure 11).

Weights of objectives

Gain Ratio: 0.75 Delivery Date: 0.25

Figure 11. Weights of objectives

Step 6: The route is constructed by Dijkstra's algorithm to find the shortest path among the cities. After this solution process is completed, the routing is created. Along with the traffic information of the created route, the Google map is displayed to the decision-maker (see Figure 11).

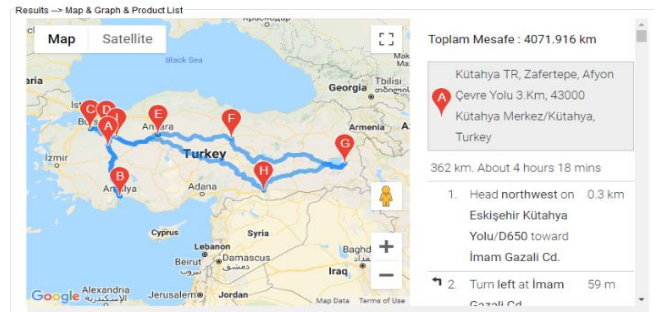


Figure 12. Display of the determined route

Step 7: After the DSS is run, the selected products, the amount of that product, and the routing are obtained. These results are presented to the decision-maker. This report provides the decision-maker with assistance for the management of operative activities and processes.

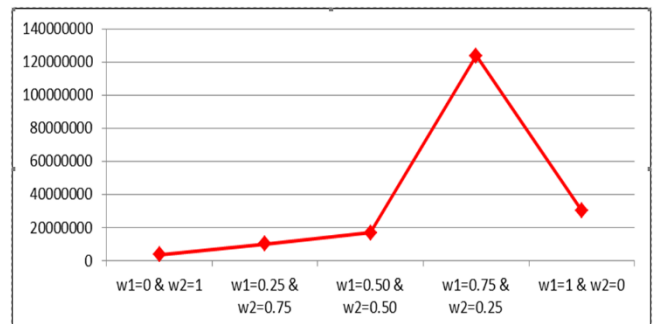


Figure 13. Sensitivity analysis based on objective weights

The screen output based on the sample problem is presented in Figure 13. Thus, the factory management decides to load and route the container according to the obtained results. As illustrated in Figure 13, the maximum fitness value is obtained at w1=0.75 and w2=0.25.

7. CONCLUSIONS AND FUTURE WORK

This research examined the Porcelain Container Loading Problem (PCLP) in Kütahya Porselen Industry Incorporated. Due to the NP-hardness of our model, a multi-objective genetic algorithm (GA) approach was proposed in order to load the container, considering two objective functions such as maximization of both product profitability and delivery priority simultaneously. The decision support system (DSS) software based on the multi-objective GA approach was developed to obtain prompt and high-quality solutions for the PCLP. This software was coded in the JAVA programming language. With the help of the software, decision-makers do not need to know any methods to obtain the results. The parameters of the multi-objective GA affect

the obtained results. Therefore, in order to determine the appropriate parameters, we conduct tuning by using an experimental design. Sensitivity analysis was executed to test the effects of the objectives' weights on the obtained results. This problem needs to be solved for future research to be compared with the results obtained from other methods. The different objective functions and constraints are added to the model.

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