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ORIGINAL PAPER

A LOGISTIC OPTIMIZATION FOR THE VEHICLE ROUTING PROBLEM THROUGH A CASE STUDY IN THE FOOD INDUSTRY

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ABSTRACT. **Background:** In this study, the food delivery problem faced by a food company is discussed. There are seven different regions where the company serves food and a certain number of customers in each region. The time of requesting food for each customer varies according to the shift situation. This type of problem is referred to as a vehicle routing problem with time windows in the literature and the main aim of the study is to minimize the total travel distance of the vehicles. The second aim is to determine which vehicle will follow which route in the region by using the least amount of vehicle according to the desired mealtime.

Methods: In this study, genetic algorithm methodology is used for the solution of the problem. Metaheuristic algorithms are used for problems that contain multiple combinations and cannot be solved in a reasonable time. Thus in this study, a solution to this problem in a reasonable time is obtained by using the genetic algorithm method. The advantage of this method is to find the most appropriate solution by trying possible solutions with a certain number of populations.

Results: Different population sizes are considered in the study. 1000 iterations are made for each population. According to the genetic algorithm results, the best result is obtained in the lowest population size. The total distance has been shortened by about 14% with this method. Besides, the number of vehicles in each region and which vehicle will serve to whom has also been determined. This study, which is a real-life application, has provided serious profitability to the food company even from this region alone. Besides, there have been improvements at different rates in each of the seven regions. Customers' ability to receive service at any time has maximized customer satisfaction and increased the ability to work in the long term.

Conclusions: The method and results used in the study were positive for the food company. However, the metaheuristic algorithm used in this study does not guarantee an optimal result. Therefore, mathematical models or simulation models can be considered in terms of future studies. Besides, in addition to the time windows problem, the pickup problem can also be taken into account and different solution proposals can be developed.

Key words: vehicle routing problem, time windows, optimization, metaheuristic algorithm, genetic algorithm.

INTRODUCTION

Companies can be advantageous over their competitors only by increasing the added value of their products and services by delivering these services to their customers faster. In other words, companies have to better control their product prices, costs, and productivity to gain an advantage over their competitors. Companies should also increase customer service satisfaction by preventing total delays with a well-planned logistics distribution channel to be at the forefront in their sector [Subramanian et al. 2013].

Since the majority of the total logistics costs of companies arise from distribution costs, the effective and efficient use of distribution equipment and personnel has become an important area of interest for business managers. In this respect, finding the most suitable route for a vehicle reduce distribution costs and increase the quality of the service offered to customers. This subject

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is referred to as a vehicle routing problem (VRP) in the literature [Gendreau et al. 2008].

The problem of vehicle routing is a problem of drawing a route, starting from a single point that allows all points to be visited with the shortest time and lowest cost. For a multi-system, at least one manufacturer, one customer, one vehicle, and one distribution structure are required for vehicle routing. Multiple input variables constitute important parameters in determining the routes according to the goal value of the total system. Therefore, the routing problem is a difficult optimization problem to calculate the results under variable inputs [Adamski 2015].

In the literature, many methods have been developed to find solutions to VRPs. There are mathematical models in different studies in the literature. In cases where mathematical models are inadequate, it is possible to talk about a wide variety of algorithms developed using heuristic and metaheuristic methods.

Metaheuristic solutions constitute the tools used to find solutions to problems at appropriate times. However, these methods obtain approximate values instead of finding the best solution value. Tabu search algorithm [Ting et al. 2017], variable neighborhood search [Todosijević et al. 2017], simulated annealing [Du et al. 2017], iterated local search [Uchoa et al. 2017], greedy randomized adaptive search procedure [Sörensen and Schittekat 2013], genetic algorithm [Hassanzadeh and Rasti-Barzoki 2017], memetic algorithm [Qi et al. 2015] and ant colony optimization [Du et al. 2017] are the most commonly used metaheuristic techniques.

Heuristic methods are iterative solution methods that consist of an intelligent combination of heuristic algorithms with different properties to find the best results in the solution area. Time-oriented nearest-neighbor heuristic [Hsu et al. 2007], iterative route construction and improvement algorithm [Figliozzi 2010], continuous forecasting model [Saberi and Verbas 2012], deterministic local search [Felipe et al. 2014], fuzzy inference algorithm [Jovanovic et al. 2014], heterogeneous adaptive neighbor search [Koç et al. 2014], evolutionary local search [Zhang et al. 2015], Clarke and Wright savings algorithm and density clustering algorithm [Erdoğan and Miller-Hooks 2012], lantime algorithm [Wen and Eglese 2015] and nearest neighbor algorithm [Suzuki and Kabir 2015] are some of the heuristic techniques used in vehicle routing problem.

There are many vehicle routing methodologies based on mathematical programming techniques. Mixed-integer linear programming [Gajanand and Narendan 2013], linear programming [Franceschetti et al. 2013], integer programming [Zhu et al. 2014], mixed-integer nonlinear programming [Glock and Kim 2015] and statistical method [Velázquez-Martínez et al. 2016].

Most of the above-mentioned studies are focused on the classical network design rather than specific vehicle routing problems with time windows. In this study, firstly we are focusing on the real-life problem considering multi-vehicle routing of daily delivery for lunch meal that a company is encountered. Secondly, time windows constraint is considered since each customer needs their lunch at different times. These objectives are considered using a genetic algorithm which is a mostly used method for NP-hard problems.

The remainder of the paper is organized as follows. Section 2 provides brief information about vehicle routing problems. The genetic algorithm which is used in this study is provided in Section 3. The proposed vehicle routing problem and application results are detailed in Section 4. Section 5 presents the conclusion and future research directions.

VEHICLE ROUTING PROBLEM

VRP was first introduced to the literature in 1959 by Dantzig and Ramser. In these studies, the authors focused on the problem of gasoline distribution to gas stations and established the first mathematical programming model to solve the problem. Later in 1964, Clark and Wright proposed an intuitive solution to the problem, but after this study, interest in VRP has grown even more in the literature. VRP is one of the optimization problems on which most methods are developed [Dantzig and Ramser 1959].

VRP is finding the best route a vehicle should follow to reduce transportation costs and increase customer service. According to another definition; VRP is the problem of designing optimum distribution/collection routes of vehicles assigned to serve geographically dispersed customers from one or more warehouses. VRP is the heart of distribution management. The simplest form of VRP is called Classical VRP [Khouadjia et al. 2012]. In Classic VRP:

1. Each city is visited only once.
2. Each vehicle starts and ends its route in the same warehouse.
3. There are restrictions on the number and configuration of routes.

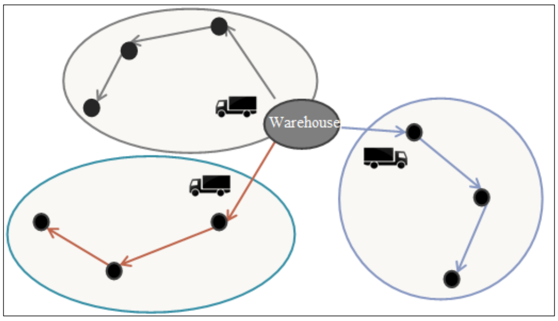
Constraints other than these basic constraints vary according to the nature of the problem. The problem of distribution of consumer goods from factories to retailers is a good and easy-to-understand example problem for VRP. Factories are supply centers, and customers are demand centers.

The VRP is a widely known integer programming problem that falls into the class of NP-hard problems where the computational power required to solve the problem increases exponentially with the size of the problem. In such problems, it is aimed to find approximate results to reach the right result quickly. This task is usually accomplished using a variety of metaheuristic methods that try to understand the nature of the problem. In this study, the genetic algorithm metaheuristic which is frequently used in the solution of NP-hard problems is used.

In the literature, VRP problems are classified according to many basic types. Most important ones; capacity-constrained, distance-constrained, time windows, distribution, and pickup VRPs. Subtypes of each basic type with additional constraints and different features are also included in the literature. The VRP type that is considered in this study is the time window distribution for multiple-vehicle delivery VRP. Brief information about this problem is given in the following section.

MULTIPLE-VEHICLE DELIVERY ROUTING PROBLEM WITH TIME WINDOWS

In this method, the needs of the customers in the network are tried to be met by using a large number of vehicles. After the demands of the customers are loaded in the network by the vehicle capacities, the vehicles reach the points on the determined route at the same time, meet the demands and return to the warehouse again. The difference between multi-vehicle vehicle routing and single-vehicle routing is that it requires as many vehicles as the number of routes in the network. This method meets the demands faster than other methods. Each transport request must be served within a predetermined time window (this constraint is called a time window). For this purpose, it is valid in cases where time constraints are important. The solution to the problem requires assigning the transportation demands to the vehicles and finding the route for each vehicle that minimizes the total cost [Laporte, 2009]. In this study, the multi-vehicle routing problem is discussed and an example of this problem type is provided in Figure 1.



Source: Khouadjia et al. 2012

Fig. 1. Multi-Vehicle Routing Problem

GENETIC ALGORITHM

The Genetic Algorithm (GA) involves the application of selection, crossover, and mutation processes to a population of individuals. Following the application of these procedures, a new population is created. The old population and the new population are exchanged for each other and each individual has its regulated value. The newly formed population is selected according to this regulated value and more compatible populations are tried to be formed in each newly created population.

GAs are particularly used in the areas of optimization, automated, mechanical learning, finance, marketing, vehicle routing, scheduling, assembly/disassembly line balancing, plant layout, and system reliability. The basic characteristics of GAs can be listed as follows [Zames et al. 1981];

- Poor solutions tend to disappear while good solutions tend to be used to create better solutions as the population evolves from generation to generation.
- They scan not the whole solution space only part of it.
- They reach a possible solution in a shorter time by doing an active search.
- They do not stick to local best solutions by simultaneously examining a population of solutions.

GAs first creates an initial population of individuals coded by the notation specified in the solution steps. Each chromosome in the initial population represents a possible solution to the problem. Each chromosome has a conformity value indicating the quality of the solution it encodes. The basic working logic of GAs is based on the proliferation of chromosomes with better conformity values, just like in the evolutionary process.

Selection is the process of selecting individuals of a new generation from the existing population according to the selection method chosen. The crossover operator is one of the substantial parameters that affect the performance of the GAs. Crossover creates new offspring by manipulating selected genes in the parent. Following the crossover operation, some of the chromosomes are mutated to increase the diversity of the chromosomes in the generation. The purpose of this process is to identify changes within the population. During the mutation process, the number of genes on the chromosome remains constant.

USE OF GENETIC ALGORITHM IN VRP

In this section, an application related to VRP has been made. The problem definition, the design phase of GA, and the results obtained are given in detail in the following sub-sections.

Problem Definition

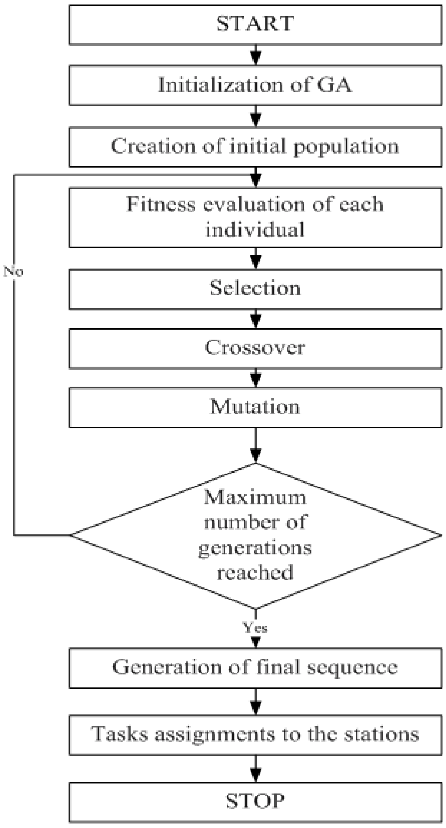
Several numerical network designs related to the VRPs are developed in the relevant literature to improve the near-optimal route for vehicles as discussed in the introduction section.

This study focused on the delivery of lunch meal food of a Food Company (FC) to various retailers in a variety of locations using the general type of vehicles. The focused problem can be described as a variant of VRP because of different service times. FC is located to the near of city center and has served 71 customers. Customer distance to the FC and the region of the vehicles are shown in Appendix-I. 7 regions and thus 7 routes are considered for this study. The customers need the foods at specific times. Minimization of the route cost increases Company's profitability. Thus, the first objective of this study is to minimize the total distances for all vehicles.

As it can be figured out from the problem, there may many different delivery options due to the nature of the problem. As an example, 11 customers are included in Region 1 means 11 different combination of the delivery route is possible for Route-1 vehicles. This combination is different for each region. To cope with the best delivery for each route, a genetic algorithm solution is provided in the following section. Thus, the second objective of this study is to find out which vehicle will serve which customer.

Design of the Genetic Algorithm

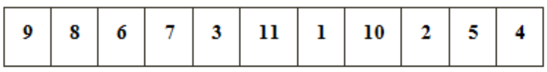
The definition of the GA was detailed in section 3. In this section, the design phase of the genetic algorithm used in the study is given. The flow diagram of this algorithm is provided in figure 2.



Source: Zames et al. 1981

Fig. 2. Flowchart of GA

The solutions in GAs are encoded as chromosomes based on the features of the problem. Chromosomes are usually constructed by using alphabets, integers, binary digits, or other characters. The structure of a chromosome for Route-1 is given in Figure 3. This chromosome involves the permutation of customer numbers and represents a possible delivery route.



Source: own work

Fig. 3. Structure of a chromosome for Route-1

The objective function of this study is to find the shortest routes for each region. While these routes are determined, each route can only be served by one vehicle and the route of the vehicles must start and end in the warehouse. However, the number of vehicles can be increased according to the desired mealtime. With the objective function, it is aimed to reduce costs by saving time, and it is aimed to ensure the highest level of customer satisfaction by meeting the demands of the customers on time. As mentioned before, customers want their meals at a certain time. In this direction, the genetic algorithm performance criteria selected for the solution were tested with different replications, and the best solution was reached, and how the genetic algorithm criteria affect the solution was revealed. It was stated in the study that there are 7 different routes. While explaining the solution method, instead of showing the solution separately for each route, only the solution for route 1 is shown. However, the findings obtained for all routes are given in Table 5 at the end of the study.

The data of 11 customers that FC distributes on Route-1 are given in the tables below. The distance matrix of the customers is given in Table 1 as km. The time interval values that customers want to receive service are given in Table 2. The travel times of the customers to each other are given in Table 3. The service time of the vehicles is fixed and 10 minutes for each customer. Accordingly, with MATLAB R15a, the data were encoded using Windows 10, 8GB RAM, 2.7 GHz (i5) computer, and the steps of the genetic algorithm were applied. The results obtained were presented in the next section.

Results of the genetic algorithm

The stages of the genetic algorithm were previously given in Figure 1. In the coding stage, permutation coding is used, single-point crossover for the crossover operator, and the mutation of two neighboring genes for mutation was applied. The sum of the distances is taken into account for the fitness function. The roulette wheel method, which is frequently used in the genetic algorithm, has been chosen in chromosome selection. Population size was considered as 10, 30, and 50 in the study. 1000 iterations were made for each population and this number was taken into account as the stopping criterion. The values obtained for all population sizes after running the program are given in Table 4.

Table 4 shows the results of the study. 1000 iterations were made for each population. The shortest distance obtained was 57.4 km with 10 population sizes. The shortest route length was seen after the 246th iteration in the algorithm running 1000 iterations.

The value did not change in subsequent iterations. The graph of this iteration is given in Figure 4. The most suitable route for this population is 1-2-6-5-11-9-10-8-7-3-4. The population size was increased in the second stage. It was observed that the total distance also increased despite the increasing population size. This value was seen after 84th iterations and did not change until 1000 iterations. Finally, the algorithm has been tested for a population size of 50 and it has been observed that the total distance increases again. As a result, the shortest path was obtained in the smallest population size and after 246th iterations. An improvement of approximately 14% was seen with the genetic algorithm as the total distance

Table 1. The distances of the customers on Route-1 to each other

Distance (km)	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**C_8**	**C_9**	**C_{10}**	**C_{11}**
C_1	0	2	2	4	5	3	4	5	2	3	1
C_2	2	0	4	4	1	5	5	1	4	3	2
C_3	2	4	0	1	1	2	5	3	4	2	4
C_4	4	4	1	0	4	3	4	1	2	5	2
C_5	5	1	1	4	0	1	2	6	2	2	3
C_6	3	5	2	3	1	0	5	4	5	2	3
C_7	4	5	5	4	2	5	0	1	4	5	3
C_8	5	1	3	1	6	4	1	0	2	3	5
C_9	2	4	4	2	2	5	4	2	0	2	5
C_{10}	3	3	2	5	2	2	5	3	2	0	1
C_{11}	1	2	4	2	3	3	3	5	5	1	0

Source: own work

Table 2. Time intervals that customers on Route-1 want the service time

Service time	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**C_8**	**C_9**	**C_{10}**	**C_{11}**
Start	08:00	09:45	11:00	12:00	11:30	10:00	10:30	9:30	08:00	08:30	12:00
End	11:45	12:15	13:15	13:00	13:30	10:30	11:40	10:30	12:45	12:30	13:15

Source: own work

Table 3. Travel times of customers on Route-1 relative to each other

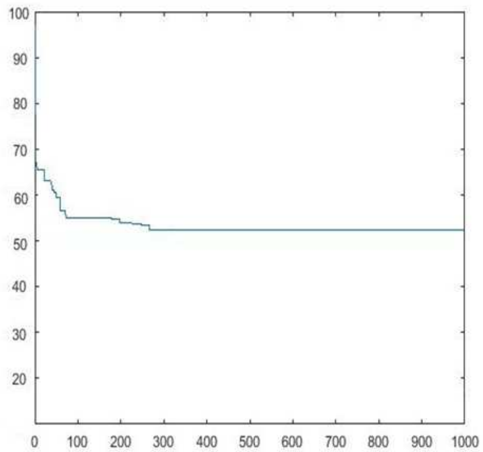
Duration (min)	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**C_8**	**C_9**	**C_{10}**	**C_{11}**
C_1	0	5	5	10	12	7	10	12	5	7	3
C_2	5	0	10	10	3	12	12	3	10	7	5
C_3	5	10	0	3	3	5	12	7	10	5	10
C_4	10	10	3	0	10	7	10	3	5	12	5
C_5	12	3	3	10	0	3	5	14	5	5	7
C_6	7	12	5	7	3	0	12	10	12	5	7
C_7	10	12	12	10	5	12	0	3	10	12	7
C_8	12	3	7	3	14	10	3	0	4	7	12
C_9	5	10	10	5	5	12	10	4	0	4	12
C_{10}	7	7	5	12	5	5	12	7	4	0	3
C_{11}	3	5	10	5	7	7	7	12	12	3	0

Source: own work

Table 4. Results of the genetic algorithm for Route-1

Population size	10	30	50
Iteration number	1000	1000	1000
Mutation rate	0.8	0.9	0.01
Crossover rate	0.2	0.05	0.5
Total shortest distance (km)	57.4	65.3	74.9
Suitable route	1-2-6-5-11-9-10-8-7-3-4	1-10-8-5-4-9-2-6-7-3-11	9-8-6-7-3-11-1-10-2-5-4
Convergence iteration number	246	84	48

Source: own work



Source: own work

Fig. 4. Convergence graph for Route-1.

In the study, the shortest path calculation for a FC is shown for Route-1. As seen in Appendix-I, there are 7 different routes in total in the study. Using the same steps for each route, a solution was found with the genetic algorithm. The shortest route and improvement rates for all routes are given in Table 5.

In the study, in addition to the route calculation for 7 different routes, how many vehicles should be for each route and which vehicle will serve which customers were added as constraints. Accordingly, an additional vehicle for each route has been added to the system. Only one vehicle service can be continued on the last route. Table 6 shows which vehicle will serve which customers for each route.

Table 5. Shortest route and recovery rates for all routes

Route	Previous total distance (km)	After total distance (km)	Delivery order within the route	Improvement rate (%)
Route-1	65.4	57.4	1-2-6-5-11-9-10-8-7-3-4	13.9
Route-2	53.3	46.3	9-12-1-3-5-8-2-11-4-10-7-6	15.1
Route-3	10.9	9.8	4-10-3-13-5-12-6-1-11-2-8-7-9	11.3
Route-4	64.8	54.1	4-6-5-1-2-3-8-7	19.8
Route-5	160.6	146.6	4-2-7-11-13-8-10-5-15-6-12-3-9-1-14	9.6
Route-6	21.2	17.3	5-7-2-8-6-1-3-4-9	22.4
Route-7	12.4	10.7	2-3-1	16.4

Source: own work

Table 6. The customer that the vehicles will serve

Routes	Vehicles	Customers	Living time
Route-1	1	1-2-6-5-11	08:00
	2	9-10-8-7-3-4	08:00
Route-2	1	9-12-1-3-5-8	08:00
	2	2-11-4-10-7-6	08:00
Route-3	1	4-10-3-13-5-12-6	09:45
	2	1-11-2-8-7-9	08:45
Route-4	1	4-6-5-1	11:30
	2	2-3-8-7	09:00
Route-5	1	4-2-7-11-13-8-10-5-15	08:45
	2	6-12-3-9-1-14	09:30
Route-6	1	5-7-2-8-6	10:50
	2	1-3-4-9	08:30
Route-7	1	2-3-1	09:00

Source: own work

APPENDIX-I

C	S	F	D (km)	R	C	S	F	D (km)	R
C_1	08:00	11:45	29,6		C_1	09:45	11:30	19,7	
C_2	09:45	12:15	32,2		C_2	08:00	12:00	23,1	
C_3	11:00	13:15	33,1		C_3	11:00	12:00	23	
C_4	12:00	13:00	32,5		C_4	09:30	11:00	20,5	
C_5	11:30	13:30	31,3		C_5	11:30	12:30	19,8	
C_6	10:00	10:30	25,3	R_1	C_6	12:00	13:30	20,1	
C_7	10:30	11:40	26,1		C_7	11:45	12:45	19,6	R_2
C_8	09:30	10:30	29,2		C_8	12:30	13:30	19,7	
C_9	08:00	12:45	29,9		C_9	08:30	10:00	23,1	
C_{10}	08:30	12:30	29,8		C_{10}	09:45	10:30	18,9	
C_{11}	12:00	13:15	34,8		C_{11}	08:45	10:00	23,3	
C_1	08:45	10:00	1,1		C_{12}	09:00	11:00	19,5	
C_2	11:00	12:00	0,65		C_1	12:00	13:00	28,2	
C_3	11:15	12:30	2,1		C_2	11:30	12:30	25,7	
C_4	09:45	11:00	0,35		C_3	11:45	12:30	48	
C_5	12:00	13:30	0,55		C_4	09:00	10:30	38,8	
C_6	12:30	13:30	3,5		C_5	11:30	12:30	39,9	R_4
C_7	12:00	13:00	3,6	R_3	C_6	11:00	13:00	44,8	
C_8	11:15	12:30	4,5		C_7	12:30	13:30	24,3	
C_9	12:30	13:30	0,9		C_8	12:00	12:45	20,3	
C_{10}	10:00	11:30	0,95		C_1	11:30	13:00	24,3	
C_{11}	09:30	11:00	2,7		C_2	09:30	11:00	17,9	
C_{12}	12:15	13:30	0,2		C_3	10:15	11:30	18,3	
C_{13}	11:45	12:45	1,5		C_4	08:45	09:45	19,6	
C_1	08:30	11:00	5		C_5	11:45	13:00	20,1	
C_2	11:45	12:30	10,4		C_6	09:30	11:00	18,5	
C_3	10:30	13:00	5,7		C_7	09:45	12:0	18,8	
C_4	11:30	13:30	6,5		C_8	11:00	12:00	19,5	R_5
C_5	10:50	12:30	5,5	R_6	C_9	10:30	11:30	20,6	
C_6	12:30	13:30	5,3		C_{10}	11:30	13:00	23,6	
C_7	11:30	13:00	12		C_{11}	10:15	11:00	19,7	
C_8	12:00	13:30	14,5		C_{12}	09:45	11:00	25,8	
C_9	11:45	12:30	13,3		C_{13}	10:30	11:30	17,9	
C_1	09:30	11:00	14,4		C_{14}	12:00	13:30	20,1	
C_2	10:00	11:30	17,3	R_7	C_{15}	12:30	13:30	22,1	
C_3	09:00	10:00	15,3						

C: Customer, S: Service Start, F: Service Finish, D: Customer distance to the FC, R: Delivery region/route.

CONCLUSIVE REMARKS

Transportation has an important share in the activities in the field of logistics. Improvements to be made on the duration and cost of transportation positively affect the total logistics activities. Planning the vehicles most appropriately can complicate the problem and turn it into a problem that cannot be solved in a reasonable time. For the solution of these and similar problems, it is tried to obtain a solution in a reasonable time with metaheuristic algorithms.

In this study, the VRP for a food company is discussed. Currently, this business serves 7 different regions. Every customer in each region requests meals at different times. Therefore, the business wants to know which customer will provide the most appropriate service with which vehicle. Genetic algorithm, one of the metaheuristic algorithms, was used in the study to solve this problem. With this algorithm, different numbers of populations were repeated for certain times, and the shortest total distance was found. However, the same method was used to determine which vehicle will serve on which route. In the study, it was observed that significant improvements were made compared to the current situation. Accordingly, the findings obtained in the study positively affected the profitability of the company because of shorter delivery distances. Moreover, increased customer satisfaction can also be considered as a positive effect for long-term profitability. The metaheuristic algorithm used in the study does not give the most optimal result due to the nature of the problem.

Therefore, mathematical models or simulation algorithms can be considered as future studies.

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REFERENCES

Adamski A., 2015. Routing problems based on HILS system platform, LogForum, 11(1). http://doi.org/10.17270/J.LOG.2015.1.8

Campbell A.M., Savelsbergh M., 2005. Decision support for consumer direct grocery initiatives, Transportation Sciences, 39 (3), 313-327. http://doi.org/10.1287/trsc.1040.0105

Dantzig G.B., Ramser J.H., 1959. The truck dispatching problem. Management Science, 6(1), 80–91, http://doi.org/10.1287/mnsc.6.1.80.

Du J., Li X., Yu L., Dan R., Zhou J., 2017. Multi-depot vehicle routing problem for hazardous materials transportation: A fuzzy bilevel programming. Information Sciences, 399, 201–218, http://doi.org/10.1016/j.ins.2017.02.011.

Erdoğan S., Miller-Hooks E., 2012. A green vehicle routing problem. Transportation Research Part E: Logistics and Transportation Review, 48(1), 100-114. http://doi.org/10.1016/j.tre.2011.08.001

Felipe Á., Ortuño M.T., Righini G., Tirado G., 2014. A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges, Transportation Research Part E: Logistics and Transportation Review, 71, 111-128. http://doi.org/10.1016/j.tre.2014.09.003

Figliozzi M., 2010. Vehicle routing problem for emissions minimization. Transportation Research Record: Journal of the Transportation Research Board, (2197), 1-7. http://doi.org/10.3141/2197-01

Franceschetti A., Honhon D., Van Woensel T., Bektaş T., Laporte G., 2013. The time-dependent pollution-routing problem. Transportation Research Part B: Methodological, 56, 265-293.

Gendreau M., Iori M., Laporte G., Martello S., 2008. A Tabu search heuristic for the vehicle routing problem with two-dimensional loading constraints, Networks: An International Journal, 51(1), 4-18. http://doi.org/10.1002/net.20192

Gajanand M.S., Narendran T.T., 2013. Green route planning to reduce the environmental impact of distribution, International Journal of Logistics Research and Applications, 16(5), 410-432. http://doi.org/10.1080/13675567.2013.831400

Glock C.H., Kim T., 2015. Coordinating a supply chain with a heterogeneous vehicle fleet under greenhouse gas emissions, The International Journal of Logistics Management, 26(3), 494-516. http://doi.org/10.1108/IJLM-09-2013-0107

Govindan K., Jafarian A., Khodaverdi R., Devika K., 2014. Two-echelon multiple vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food, International journal of production economics, 152, 9-28. http://doi.org/10.1016/j.ijpe.2013.12.028

Hasani A., Zegordi S.H., Nikbakhsh E., 2012. Robust closed-loop supply chain network design for perishable goods in agile manufacturing under uncertainty, International journal of production research, 50 (16), 4649-4669. http://doi.org/10.1080/00207543.2011.625051

Hassanzadeh A., Rasti-Barzoki M. 2017. Minimizing total resource consumption and total tardiness penalty in a resource allocation supply chain scheduling and vehicle routing problem. Applied Soft Computing Journal, 58, 307–323, https://doi.org/10. 1016/j.asoc.2017.05.010.

Hsu C.I., Hung S.F., Li H.C., 2007. Vehicle routing problem with time-windows for perishable food delivery, Journal of Food Engineering, 80(2), 465-475. http://doi.org/10.1016/j.jfoodeng.2006.05.029

Jovanović A.D., Pamučar, D.S., Pejčić-Tarle S., 2014. Green vehicle routing in urban zones–A neuro-fuzzy approach, Expert Systems with Applications, 41(7), 3189-3203. http://doi.org/10.1016/j.eswa.2013.11.015

Khouadjia M.R., Sarasola B., Alba E., Jourdan L., Talbi E.G. 2012. A comparative study between dynamic adapted PSO and VNS for the vehicle routing problem with dynamic requests, Applied Soft Computing Journal, 12(4), 1426–1439. http://doi.org/10.1016/j.asoc.2011.10.023

Koç Ç., Bektaş T., Jabali O., Laporte G. 2014. The fleet size and mix pollution-routing problem, Transportation Research Part B: Methodological, 70, 239-254.

Laporte G., 2009, Fifty years of vehicle routing, Transportation science, 43(4), 408-416. http://doi.org/10.1287/trsc.1090.0301

Osvald A., Stirn L.Z., 2008. A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food, Journal of Food Engineering, 85 (2), 285-295. http://doi.org/10.1016/j.jfoodeng.2007.07.008

Prindezis N., Kiranoudis C.T., Marinos-Kouris D., 2003. A business-to-business fleet management service provider for central food market enterprises, Journal of Food Engineering, 60 (2), 203-210. http://doi.org/10.1016/S0260-8774(03)00041-4

Qi Y., Hou Z., Li H., Huang J., Li X., 2015. A decomposition based memetic algorithm for multi-objective vehicle routing problem with time windows, Computers & Operations Research, 62(3), 61–77, http://doi.org/10.1016/j.cor.2015.04.009.

Saberi M., Verbas İ.Ö., 2012. Continuous approximation model for the vehicle routing problem for emissions minimization at the strategic level, Journal of Transportation Engineering, 138(11), 1368-1376.

Schmid V., Doerner K.F., Hartl R.F., Savelsbergh M.W.P., Stoecher W., 2009. A hybrid solution approach for ready-mixed concrete delivery, Transportation Sciences, 43 (1), 70-85. http://doi.org/10.1287/trsc.1080.0249

Sorensen K., Schittekat P., 2013. Statistical analysis of distance-based path relinking for the capacitated vehicle routing problem, Computers and Operations Research, 40(12), 3197–3205, https://doi.org/10.1016/j.cor.2013.02.005.

Subramanian A., Uchoa E., Ochi L.S., 2013. A hybrid algorithm for a class of vehicle routing problems, Computers & Operations Research, 40(10), 2519–2531. http://doi.org/10.1016/j.cor.2013.01.013

Suzuki Y., Kabir, Q.S., 2015. Green Vehicle Routing for Small Motor Carriers, Transportation Journal, 54(2), 186-212. http://doi.org/10.5325/transportationj.54.2.0186

Ting C.K., Liao X.L., Huang Y.H., Liaw R.T. 2017. Multi-vehicle selective pickup and delivery using metaheuristic algorithms. Information Sciences, 406–407, 146–169, http://doi.org/10.1016/j.ins.2017.04.001.

Todosijević R., Hanafi S., Urošević D., Jarboui B., Gendron B., 2017. A general variable neighborhood search for the swap-body vehicle routing problem. Computers & Operations Research, 78, 468–479, http://doi.org/10.1016/j.cor.2016.01.016.

Tarantilis C.D., Kiranoudis C.T., 2001. A meta-heuristic algorithm for the Efficient distribution of perishable foods, Journal of Food Engineering, 50 (1), 1-9. http://doi.org/10.1016/S0260-8774(00)00187-4

Tarantilis C.D., Kiranoudis C.T., 2002. Distribution of fresh meat, Journal of Food Engineering, 51 (1), 85-91. http://doi.org/10.1016/S0260-8774(01)00040-1

Uchoa E., Pecin D., Pessoa A., Poggi M., Vidal T., Subramanian A. 2017. New benchmark instances for the Capacitated Vehicle Routing Problem, European Journal of Operational Research, 257(3), 845–858, http://doi.org/10.1016/j.ejor.2016.08. 012.

Velázquez-Martínez J.C., Fransoo J.C., Blanco E.E., Valenzuela-Ocaña K.B., 2016, A new statistical method of assigning vehicles to delivery areas for CO2 emissions reduction. Transportation Research Part D: Transport and Environment, 43, 133-144. http://doi.org/10.1016/j.trd.2015.12.009

Ying W., Ying Y.L., 2012. Optimization model of refrigerated food transportation. In: Proceedings of International Conference of Service Systems and Service Management, Beijing, 220-224. http://doi.org/10.1109/ICSSSM.2012.6252224.

Wen L., Eglese R. 2015. Minimum cost VRP with time-dependent speed data and congestion charge. Computers & Operations Research, 56, 41-50. http://doi.org/10.1016/j.cor.2014.10.007

Zhang Z., Wei L., Lim A. 2015. An evolutionary local search for the capacitated vehicle routing problem minimizing fuel consumption under three-dimensional loading constraints, Transportation Research Part B: Methodological, 82, 20-35. http://doi.org/10.1016/j.trb.2015.10.001

Zames G., Ajlouni N.M., Ajlouni N.M., Ajlouni N.M., Holland J. H., Hills W.D., Goldberg D.E., 1981. Genetic algorithms in search, optimization and machine learning. Information Technology Journal, 3(1), 301-302.

Zhu X., Garcia-Diaz A., Jin M., Zhang Y., 2014. Vehicle fuel consumption minimization in routing over-dimensioned and overweight trucks in capacitated transportation networks, Journal of Cleaner Production, 85, 331-336. http://doi.org/10.1016/j.jclepro.2013.10.036

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