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RESEARCH ARTICLE

A Sectoral Application for Green Vehicle Routing Problem Optimization with Capacity Constrained and Heterogeneous Fleet*

Furkan Dişkaya[1], Sait Erdal Dinçer[2]

[1](Asst. Prof.), İstanbul Beykent University, Industrial Engineering, İstanbul, Türkiye
[2] (Prof. Dr.), Marmara University, Department of Econometrics, İstanbul, Türkiye

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ABSTRACT
The vehicle routing problem (VRP), which is a type of traveling salesman problem (TSP), is a combinatorial optimization problem which determines the shortest route distribution from a central warehouse to customer points in certain locations. Today, global climate change resulting from high greenhouse gas emissions and the rapid decrease in natural resources have begun to threaten life as well as the sustainability of our economic structures. For this purpose, businesses have begun to prioritize to the concept of green logistics, which is based on the strategy of environmentally friendly activities in the production of goods and services. In this study, a mathematical model is proposed to solve the green vehicle routing problem with capacity limited and heterogeneous fleet (CHFGVRP), which is a type of vehicle routing problem under the green logistics strategy. Metaheuristic approaches produce successful solutions when solving routing problems with an NP-hard class problem structure. The presented model was developed by Ekol Inc., with the help of the Genetic Algorithm (GA) and Tabu Search (TS) metaheuristic solution approaches. It has been optimized as a real distribution operation for logistics businesses. The main purpose of the present study is assigning vehicles of different capacities of a logistics company to the most suitable loads for two different order sets, to determine the most appropriate customer point route. Thus, as transportation costs decrease thanks to fuel savings, the amount of carbon emissions released into the environment will also decrease. The results of this research will contribute to businesses which seek environmental and economic sustainability, as well as to the developing scientific literature on the subject.

Keywords: Green vehicle routing problem, genetic algorithm, tabu search

1. Introduction

Many common activities, including transportation, production, and heating, emit greenhouse gases into the atmosphere and increase the environmental restrictions to the point where they threaten the continuity of life for all living things. High carbon emissions, one of the main causes of the global climate concerns, is an extremely important problem that requires attention from the entire world.

Countries have taken action to reduce greenhouse gas emissions caused by fossil fuel use through many international agreements, such as the Paris Agreement and the Kyoto Protocol. The main purpose of these agreements is to transition to alternative energy sources in order to reduce carbon dioxide (CO_2) levels in the atmosphere and to establish a logistics management system that will enable the transportation of vehicles in a way that consumes less energy. In order for these efforts to yield results, regulations that limit the actions of both individuals and companies are extremely important. The main source of (CO_2) gas in the atmosphere, which makes up approximately 59% of greenhouse gases, is fossil fuels. Transportation is the most notable sector which contributes to this growing concern, with a high rate of 32% in total energy consumption and a share of 23% in carbon emissions (IEA Report, 2023).

Logistics management activities, which are included in all operations of supply chain management, are defined as the delivery of the material to be supplied to the final consumer as a result of activities, such as storage, production, and distribution (Waters, 2003:17). Carrying out all logistics activities while minimizing damage to the environment is referred to as green logistics

Corresponding Author: Furkan Dişkaya **E-mail:** furkandiskaya@beykent.edu.tr
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(Srivastara, 2007: 53). It is very important that logistics activities remain sustainable within the scope of the green strategy. Increasing consumption results in a scarcity of natural resources, which causes the ecological balance to deteriorate and the ecosystem to collapse. Logistics operations, which provide all the physical movement of this economic system, are extremely important for sustainable supply chain management systems (Christopher. 2011:11).

Transportation uses the most fossil fuel among logistics activities. Freight transportation, which uses the roads in the country, comprises approximately 76% of transportation activities in Turkey, 69% in the USA, and 45% in EU countries. Therefore, the effective and efficient use of such transportation remains crucial to sustainable and green logistics strategies (Çevik & Gülcan, 2011:39). Therefore, obtaining the best routes for distributing product orders according to sustainable and green principles has become a frequently studied application area for logistics management.

The traditional vehicle routing problem (VRP) is defined as determining the route of transportation activities to minimize the total time and total distance in order to supply the demands of customers at multiple points with vehicles of certain capacities from a central warehouse (Figliozzi, 2010:1). New constraints have been added, with many different models having been proposed according to the different business goals. The most common of these include: distance limited (DARP), capacity limited (CARP), distance and capacity limited (DCARP), recollection (RCARP), multiple warehouse (MWARP), and homogeneous or heterogeneous fleet (HFARP) (Akcakoca et al., 2023:3).

Unlike traditional VRP, the green vehicle routing problem (GVRP) optimizes through including such variables as fuel consumption and gas emissions in addition to the total travel length. Fuel consumption and gas emission variables are affected by a wide variety of factors, such as: travel length, vehicle speed, vehicle load, time-varying speed, and road slope. In this way, GVRP targets alternative fuel use, electric and hybrid vehicle use, and environmentally friendly routing (Lin, 2014: 1). With GVRP, distances traveled and distribution networks will be optimized, with a reduction of fuel consumption through alternative nature-friendly energy sources. Thus, natural energy resources will be consumed less, carbon emissions will decrease, and a positive contribution will be made to the problem of global warming/climate change. This goal becomes possible through an optimization of the organization of vehicle routes, distribution networks, and vehicle fleets (Bruglieri et al., 2022:2).

Operations research optimization problems can be broken down into two types: discrete and continuous. Combinatorial optimization problems, which are a type of problem with discrete decision variables, have a structure which allows for rapid results due to their solution approaches. It is possible to reach the solution by using simple linear programming methods. However, when the number of constraints and variables in the mathematical model of the problem increases according to the difficulty level of the problem, it will become a global optimization problem and enter the NP-hard problem class, which is notoriously difficult to solve (Nilsson, 2003:3). VRP falls under the combinatorial problem class. Within the literature, exact solution approaches to solve such problems have been listed as: branch and bound, branch cutting, cutting plane, and dynamic programming methods (Toth & Vigo, 2002:455). The structure of real-life VRP problems fall under the complex and large-scale NP-hard class. It is not possible to evaluate such problems in an acceptable time with definitive solution approaches. Instead, heuristic and metaheuristic methods must be used, which can provide the result closest to the optimal solution in a shorter time.

This study examines the optimization of the VRP in distribution networks, which is the activity of logistics management with the highest time and cost. For this purpose, an example application has been made on CHFGVRP, which is a type of VRP designed in accordance with the aims of the green logistics strategy. Genetic algorithm (GA) and tabu search algorithm (TS), which are metaheuristic solution methods, were used to model the solution. In practice, data from Ekol Logistics Inc.'s Adana central warehouse was used. To write the algorithm, the C# 6.0 Visual Studio 2015 programming language was used. The main purpose was to assign the vehicles of different capacities of a company operating in the logistics sector to the load in the most appropriate way for distribution planning and to calculate the most appropriate order route. The results will contribute to reducing costs, through fuel savings, and the amount of carbon emissions. Thus, this study aims to contribute to businesses that aim for a more environmentally friendly and sustainable logistics management strategy, as well as the literature on the subject.

2. Literature Review

VRP is based on the knight's tour problem posed by Leonhard Euler in 1759. The tour presented in this problem formed the basis of the traveling salesman problem (TSP). TSP is a problem that aims to produce the shortest tour which passes through each of the m points with known distances only once, at the least cost. The basis of the knight's tour and TSP is to visit each point in a single loop (Parberry, 1996:19). The first known definition of VRP was put forward by Dantzig and Ramser (Dantzig and Ramser,1959).

VRP is defined as the problem in which routes are determined that enable vehicles with known capacities to reach customer points from a warehouse by minimizing the circulation distances in order to meet a certain demand (Boz et al., 2024: 759). The Clarke and Wright Savings Algorithm was the first such proposition meant to solve this problem (Clarke and Wright, 1964). Afterwards, many different study examples were observed, with many posed for VRP by adding various goals and constraints

(Maranzana, 1964; Webb, 1968; Christofides and Eilon, 1969; Laporte et al., 1987; Lenstra et al., 1990; Laporte, 1992; Solomon et al., 1992; Fisher, 1995; Toth and Vigo, 1998; Nagy and Salhi, 2007).

GVRP differs from classical VRP by aiming to minimize the fuel consumption and total travel length of vehicles. Businesses want to reduce the gas emissions and fuel consumption values of their vehicles in order to foster an image of social responsibility within their sector and also to reduce their costs (Figliozzi, 2010:1). In recent years, there has been an increase in GVRP studies with the influence of environmental policies. Bektaş and Laporte have developed a new approach to the classical VRP as the Pollution Routing Problem, a model in which travel distance, greenhouse gas emissions, and fuel consumption are taken into account simultaneously (Bektaş and Laporte, 2011). Despite this, the first study referred to as GVRP in the literature was put forward by Erdoğan and Miller-Hooks (Erdoğan and Miller-Hooks, 2012).

Suzuki aimed to reduce greenhouse gas emissions and fuel consumption in the model it produced for heavy-duty vehicles (Suzuki, 2011). The study of Demir et al differentiated itself by developing a model for GVRP that included new constraints (Demir et al., 2011). Schneider et al. produced a model for electric vehicles (Schneider et al., 2014). Liu et al. proposed a decision model in which the carbon footprint is minimized (Liu et al., 2014). Lin et al. developed a GVRP model based on genetic algorithms (Lin et al., 2014). In the study of Kramer et al. the team proposed a limited model of speed, planning, and routing with metaheuristic algorithms (Kramer et al., 2015). Hiermann et al. introduced a GVRP model for electric vehicles with different capacities (Hiermann et al., 2016). Koç et al. proposed a model for vehicles with different fuel consumption (Koç et al., 2016). Velázquez-Martínez et al. carried out a study which aimed to reduce carbon emissions with a statistical method (Velázquez-Martínez et al., 2016). Majidi et al.introduced a time-window GVRP model that takes carbon emissions and fuel consumption into account (Majidi, et al., 2017).

Xu et al. implemented a multi-objective decision model that takes into account time window and changing vehicle speed (Xu et al., 2019). Li et al. presented a multi-objective decision model proposal for the multi-warehouse GVRP model (Li et al., 2019). Yu et al. employed an exact solution approach for a problem with a heterogeneous fleet and time window (Yu et al., 2019). Ren et al. presented the green constrained model they pioneered for a fleet consisting of electric, gasoline, and diesel vehicles (Ren et al., 2020). Abdullahi et al. proposed a new vehicle routing model, taking into account social, economic, and environmental factors (Abdullahi et al., 2021) Utama et al. proposed a solution which takes fuel and delay costs into account in green constrained problems with time windows (Utama et al., 2021). Ferreira et al. developed a mathematical model for a GVRP with discrete delivery and loading constraints (Ferreira et al., 2021). Fakhrzad et al. proposed a model to solve the green vehicle routing problem that arises in case of demand uncertainty (Fakhrzad et al., 2022). Su et al. developed a genetic algorithm-based model for a GVRP with multiple warehouses and a limited time window (Su et al., 2023). Meng et al. implemented an application for the heterogeneous green vehicle routing problem in case of different customer service demands (Meng et al., 2023).

When examining the literature, it can be seen that many different models and solution methods have been used for VRP and GVRP. According to the information obtained from studies in which metaheuristic solution methods are frequently used due to the problem structure, the following evaluations are taken as basis for the solution approach to be used in the study:

- GA and GA-based hybrid approaches have been frequently used as solution methods in studies. It was observed that they provide better results than other methods.
- For VRP, which is a permutation-based problem by nature, the most suitable approaches to permutation-based coding used to define the model are GA and TS methods.
- Since GA, semi-stochastic, and TS can be suitable for deterministic data structures, they are also suitable for all data that can be used in VRP problems.
- While GA directly benefit from the objective function for the solution, the TS method can develop a solution without the objective function. Additionally, both methods are population-based. Such similar and different features will add effectiveness and comparative richness to the solution.

3. Problem Definition and Methods

In the study, a mathematical model was proposed to solve the CHFGVRP, with metaheuristic algorithms used for the solution. Within the scope of the application, the study aimed to optimize the central warehouse Ekol Logistics Inc.'s central warehouse. The first part of this section includes the data set obtained from the business. In the second step, the mathematical model proposed for problem solving will be presented, before expressing the stages of the methods to be used in the solution.

3.1. Data Set

Data of order sets belonging to two different customer groups served by the Adana central warehouse of Ekol Logistics Inc. were used in the problem. Table 1 expresses the values of two different order sets in terms of quantity and quantity.

Table 1. *Customer Orders*

Order Set	1	2
Number of Distribution Points	161	154
Total Number of Orders (pieces)	499	372
Total Order Quantity (vw*)	39281	36306

**vw: volumetric weight = (Length x Width x Height) / 3000*

The Yandex map application was used to obtain the map and distance matrix for the customer locations where the distribution will be made. Customer location information for both order sets are illustrated in Figure 1 and 2.

Figure 1. Order Set-1 Customer Locations

Figure 2. Order Set-2 Customer Locations

The vehicle fleet information used to deliver the customer orders is included in Table 2 below.

Algorithms were written based on information received from the business. According to this:

- An average of 350-450 orders per day are distributed to approximately 130-170 order points.
- Distribution is made six days a week, between Monday and Saturday.
- Loading and unloading times of transported goods are blurred because they vary depending on the delivery point, product weight, product volume, and delivery time. According to the information received from the company, the loading process takes an average of 10 minutes and the unloading process takes an average of 15 minutes. The algorithm was written accordingly.

- The time window during which vehicles operate for delivery and return orders is scheduled between 07:30 - 19:00 each day. Depending on return orders, vehicle returns may be extended until 21:00.
- According to the information obtained from the map service, the average speed of the vehicles was recorded as 40 km/h.
- The coordinates of customer points were used to produce the distance matrix. With the help of the clustering algorithm, the points closest to each other have been grouped together and the delivery points have been marked. This was done to ensure that delivery vehicles can serve order points with a single vehicle. Since the number of points in the distribution network is very high, the distance matrix table was not expressed nor in the algorithm.
- Orders arriving at the warehouse automatically fall into the order pool after they are prepared, with the loads and averages of the vehicles being determined according to the load amount and condition of the route. As there was no algorithm or program used for this purpose in the business, the transactions are organized entirely by the intuitive planning of the employees.

Table 2. *Vehicle Fleet List*

Vehicle code	Type	Brand	Vw	Fuel Consumption (lt/km)	Carbon Emission (gr/lt)*
A_1	Light Truck	Iveco	7615	0,18	480,78
A_2	Van	Iveco	6000	0,14	373,94
A_3	Light Truck	Mercedes	10662	0,21	560,91
A_4	Light Truck	Iveco	7213	0,17	454,07
A_5	Panelvan	Fıat	5503	0,12	320,52
A_6	Truck	Mercedes	12017	0,22	587,62
A_7	Truck	Mercedes	12017	0,22	587,62
A_8	Truck	Ford	14805	0,3	801,3
A_9	Panelvan	Iveco	4990	0,11	293,81

**1 Liter of diesel = 2671 grams of* CO_2

3.2. Mathematical Model

The two main purposes of the mathematical model developed for problem solving, the application of which is included in the study, are to minimize fuel consumption and carbon emissions. According to the literature examined to produce the model, the speed of the vehicle, the time-dependent speed of the vehicle, the load of the vehicle, the slope of the road, the vehicle fleet, and the length of the trip are the main factors which affect the amounts of fuel consumption and carbon emissions. However, it was understood that the problems examined in the studies were modeled in accordance with the various conditions of the relevant country, city, and enterprise. According to the determined variables, business data will be expressed in the model as follows:

- What is the fuel consumption type of the vehicles? All of the vehicles consume fossil fuels.
- What is the capacity type of vehicle fleets? The company's vehicle fleet has a heterogeneous structure.
- Should road slopes be included in the model? Geographically, road slopes vary widely and can be neglected.
- Should the average speed and time-dependent speed of the vehicle be included in the model, depending on the traffic density? Traffic density is stochastic due to regional conditions. Therefore, fuel consumption, which may vary depending on vehicle speed, will not be a valid constraint.
- Since load weights constantly change depending on the loading and unloading frequency, is it appropriate to add them to the model? This constraint has been neglected due to the wide variety of loads carried in the enterprise and the loading and unloading operations occurring very frequently.
- Accordingly, certain sources were used in the production of the linear multi-objective mathematical model written for the CHFGVRP solution (Toth & Vigo, 2002:492; Lei et al., 2006; 957).

Parameters:
Z = Total daily working hours (hours), valid for all vehicles.
M = Average distance (km) traveled in traffic in one hour.
K_v = v ϵ V carrying capacity (vw) of the vehicle.

B_v = v ϵ V the amount of fuel your vehicle burns per km (liters).
E_v = v ϵ V The amount of carbon emissions (CO_2) produced by the vehicle per km.
T_{ij} = i ve j distance between nodes (km).
Q_i = i ϵ N \{0} total (vw) of customer's orders.
a = Fixed duration (hours) of loading to vehicles in the warehouse.
b = Fixed duration (hour) of the delivery process to customers.

Decision Variables:
x_{ijvr} = 1, if the vehicle passes through arc ij at v ϵ V, tour r ϵ R, otherwise 0
y_{ivr} = 1, if vehicle, v ϵ V, tour r ϵ R it calls at customer i, otherwise 0
q_{ijvr} = Vehicle, v ϵ V, tour r ϵ R, the total amount of load it carries on the arc ij

Sets:
N = {0,1,. . . ,N} node set (node 0 represents the warehouse, other nodes are used for customers)
A = $\{(i, j)|i, j\epsilon N\}$ arcs. (paths connecting two nodes)
V = $\{1, . . . , V\}$ vehicle set
R = $\{0, 1, . . . , N - 1\}$ a set of tours that a vehicle can take

Objective function:
Objective function 1: The total amount of fuel burned should be minimized

$$Min \sum_{i=0}^{N} \sum_{j=0}^{N} T_{ij} \sum_{v=1}^{V} \sum_{r=0}^{N-1} B_v.X_{ijvr} \tag{1.1}$$

Objective function 2: The total amount of carbon emissions produced should be minimized

$$Min \sum_{i=0}^{N} \sum_{j=0}^{N} T_{ij} \sum_{v=1}^{V} \sum_{r=0}^{N-1} E_v.X_{ijvr} \tag{1.2}$$

Restrictions:
Constraint 1: A customer should only be visited once.

$$\sum_{v=1}^{V} \sum_{r=0}^{N-1} Y_{ivr} = 1 \qquad \forall i \epsilon N \setminus \{0\} \tag{1.3}$$

Constraint 2: All nodes that have input must also have an output.

$$\sum_{j=0}^{N} X_{ijvr} = \sum_{j=0}^{N} X_{jivr} = Y_{ivr} \qquad \forall i \epsilon N, v \epsilon V, r \epsilon R \tag{1.4}$$

Constraint 3: The quantity delivered to customers should be as much as their demands.

$$\sum_{j=0}^{N} q_{jivr} - \sum_{j=0}^{N} q_{ijvr} = Q_i.Y_{ivr} \qquad \forall i \epsilon N \setminus \{0\}, v \epsilon V, r \epsilon R \tag{1.5}$$

Constraint 4: The load carried by the vehicle at any time should not exceed its capacity.

$$q_{ijvr} \leq K_v.X_{ijvr} \qquad \forall (i, j) \epsilon A, v \epsilon V, r \epsilon R \tag{1.6}$$

Constraint 5: (Total time a vehicle spends on the road) + (total delivery time of the vehicle) + (total loading time spent by the vehicle in the warehouse) ≤ It must be equal to or less than the total operating hours of the vehicle during the day.

$$\sum_{r=0}^{N-1}\sum_{i=0}^{N}\sum_{j=0}^{N} T_{ij}.X_{ijvr}/M + \sum_{r=0}^{N-1}\sum_{i=1}^{N} Y_{ivr}.b + \sum_{r=0}^{N-1}\sum_{j=1}^{N} X_{0jvr}.a \leq Z \qquad \forall v \epsilon V \tag{1.7}$$

Constraint 6: The arc variable can take the value 0 or 1.

$$x_{ijvr} \epsilon \{0,1\} \qquad \forall (i,j) \epsilon A, v \epsilon V, r \epsilon R \tag{1.8}$$

Constraint 7: The customer variable can take the value 0 or 1.

$$y_{ivr} \epsilon \{0,1\} \qquad \forall i \epsilon N, v \epsilon V, r \epsilon R \tag{1.9}$$

Constraint 8: The load or order quantity must be greater than 0.

$$q_{ijvr} \geq 0 \qquad \forall (i,j) \epsilon A, v \epsilon V, r \epsilon R \tag{1.10}$$

3.3. Methods

VRP are problems within the NP-Hard class, which means that it is very difficult to reach the exact solution value in polynomial time, that is, in an acceptable time. Therefore, it is appropriate to use heuristic and metaheuristic methods to solve such problems. Genetic Algorithm and Tabu Search methods were used in the CHFGVRP solution discussed in the application. In this section, the definition of the methods and solution steps will be presented.

*3.3.1. **Genetic Algorithm***

The genetic algorithm (GA) is an optimization solution approach modeled on natural evolution processes. This algorithm is produced by imitating the behavior of living things that adapt to natural processes at the highest level and can transmit their hereditary characteristics to future generations. As a quantitative optimization approach, it can provide very successful solutions in solving multi-objective and highly constrained problems, such as traveling salesman and scheduling, where classical optimization techniques cannot be used (Zbigniew, 1996:15). The basic features of GA, which was first developed by John Holland in 1975, can be listed as follows:

- It is applicable for discrete and continuous optimization problems.
- It can operate without getting stuck in local minimum points.
- It provides convenience in terms of parameter definition for complex and nested data structures.
- They speed up running algorithms due to their parallel working features.
- In GA, the genetic structure of the individual is called the genotype, with the external appearance consisting of the individual's genetic structure being called the phenotype. The gene sequence that is of a certain length and contains the characteristics of the individual is called a chromosome and represents the solution to the problem. Allele is the smallest unit within a chromosome and is generally represented by 0.1 (Eiben & Smith, 2003: 25).

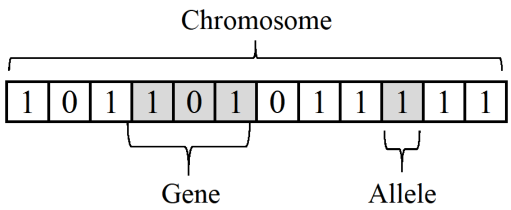

Figure 3. Order Set-2 Customer Locations

The community consisting of chromosomes that represents the alternative solution set in the problem is called the population. The fitness function represents the objective function that evaluates each chromosome in the population according to its situation. Genetic operators are operations that serve to expand the solution search area of the algorithm by producing better populations than the existing generation. Operators used for this purpose include: selection, crossover, and mutation. The basic procedures for using GA for optimization purposes are as follows (Michalewicz, 1996:17):

Step 1. Representing the problem with genetic coding,
Step 2. Producing the initial solution to express the potential solution values,
Step 3. Determining the suitability of the solution values with the fitness function,
Step 4. Producing new individuals with genetic operators,
Step 5. Determining the stopping criterion and testing the criterion. If the result is appropriate, stop the algorithm; if not, renew the process.

The GA solution stages are expressed in Figure 4 below.

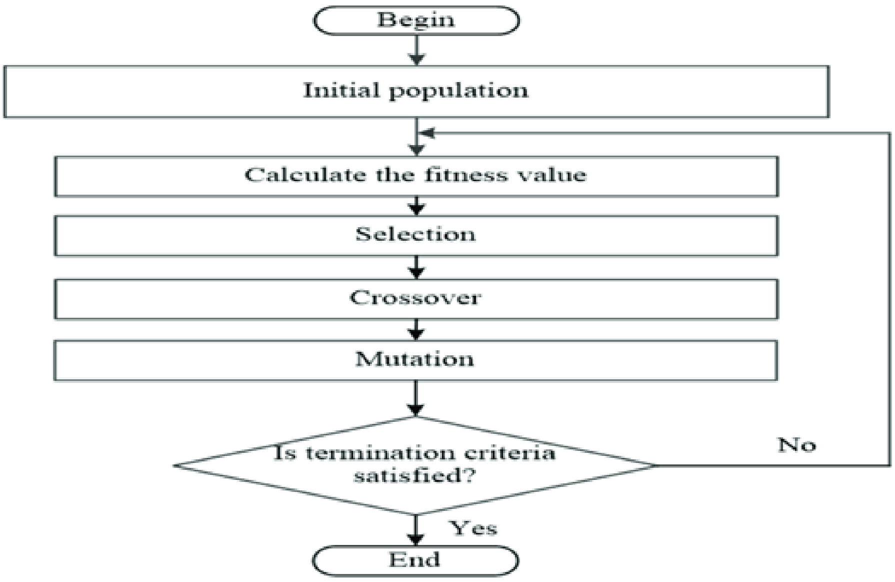

Figure 4. Genetic Algorithm Solution Stages

Step 1: The GA method starts the optimization with the coding process for the representation of the problem. The genetic coding of the problem represents the structural characteristics of the possible solution individuals (Eiben & Smith, 2003: 49). In the literature, the following coding types can be found: binary, tree, permutation, and gray coding. Permutation coding is among the most suitable for the structure of combinatorial problems, as it is in VRP. In practice, permutation coding was used for this purpose.

For example, for a seven-city VRP, it will be understood that the vehicle will visit cities 2, 6, 4, 1, 5, 3, 7, and 9 in order.

2	6	4	1	5	3	7	9

Figure 5. Chromosome:

Step 2: The initial population of random solutions is the produced. These population individuals, representing different regions within the solution space of the problem, can search from many different points at the same time. While there is no definitive technique for determining population size, choosing the problem in accordance with its type and size will increase the effectiveness of the solution (Drake & Marks, 2002:7). One of the generally accepted methods in the literature is to determine the population size as a value between [n, 2n] to express the length of the n chromosomes. According to this information, the population size was chosen to be 250.

Step 3: The fitness value is a parameter that determines the solution quality of the problem and is calculated according to the fitness function. The fitness function will calculate a value for each chromosome in the current population. In order to reduce the total distance, which is the main purpose of VRP, it is necessary to minimize the distance by changing the order depending on the genes of each chromosome within the population.

Step 4: While some of the individuals in the population will be passed on to future generations, some will disappear. This situation, referred to as natural selection, is a feature of the selection operator (Sakawa, 2002: 19). The most frequently used methods for this selection include: roulette wheel, random selection, ranked selection, tournament selection, and elitism methods.

In cases where the population volume is high, sequential, random, and roulette wheel methods provide ineffective results due to the long processes. In this case, the tournament selection method may be appropriate. Among a certain number of individuals, those with the highest fitness value are selected and passed on to future generations as parents (Eiben & Smith, 2003:84). The present study employed the double tournament method for the selection process. In addition, if every individual in the population is produced by crossing, elitism is achieved by directly adding the two best individuals in the population to the new population in order to eliminate the possibility of good individuals not being selected and leaving the solution.

Various procedures must be performed to transfer the selected parents to the next population. The genetic operators used for this purpose are: crossover and mutation. The process of obtaining new individuals with superior fitness values after combining the qualities of two parents is called crossover (Gen & Cheng, 1997:2). The crossover operator, which must be selected according to the type of coding used to define the problem, can be made via different methods, such as: single and double point, sequential, partial, regular, circular, and position-based. One of the methods frequently used in VRP problems in the literature is the single-point crossover method. It is used to cross two chromosomes with the same gene length. Selected parents are cut from a single point and exchanged in order to produce new generations. The crossover probability is chosen between 0.3 and 0.9.

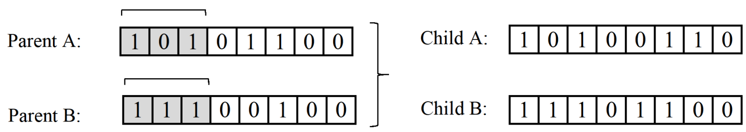

Figure 6.

The mutation operator is used to reach global best solutions without being caught by local best solutions. This process is used to include regions in the search space that cannot be reached with the crossover operator. The mutation operator, which varies depending on the chromosome coding, can be applied with different methods, including: uniform, bit substitution, two-point substitution, and inversion. When any gene for which the mutation operator is selected for VRP is transformed by the mutation process, it is necessary to make a correction to prevent the gene expressed with the same sign and number from becoming a duplicate. In such problems, the operator operation is provided by gene replacement in the general literature. This type of mutation operator is called two-point substitution mutation and was used in this study.

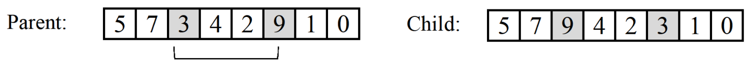

Figure 7.

Step 5: The last step to complete the GA optimization process is to determine the stopping criterion and finish the algorithm. The literature includes many criteria for this, including: a certain number of process iterations, approaching the target solution, a certain time period, and minimum improvement. The most frequently used criterion is that when a certain number of iterations are reached, the change occurs, and the target solution value is approached. For this study, it was accepted that the optimal solution should be obtained when the algorithm cycle ends for the number of generations determined as the stopping criterion in solving the problem.

*3.3.2. **Taboo Search***

The taboo search (TS) approach was first developed by Glover and Hansen to be used in solving combinatorial optimization problems (Lopez et al., 1998:317). In this approach, the word "taboo" relates to the restriction and prohibition of some inappropriate regions in the solution space of the problem. In this method, the two basic solution strategies are the neighborhood search structure and paying attention to the search projections in order to ensure diversity in each solution search without getting caught up in local optimum points. In this approach, the transition to the next solution is achieved from the most appropriate solutions within the existing neighborhood structure by performing high iterations. The best solution, if available, is selected among the best values obtained in the past. The list produced in this way from a certain number of past solutions is defined as the taboo search list (Al-Anzi & Allahverdi, 2007:84). This list is the basis of the solution and must be updated regularly so that the algorithm can work without repetition. If the best solution is obtained among the existing solution values, it is accepted, even if it is in the taboo list, and the search should continue using this renewed value. The list consisting of all subsets of the movements in the solution space and the resulting neighborhood relations is called the candidate list. The length of time that solutions included in the taboo list remain banned is called the ban period. The tolerance value will answer the questions of how much improvement is required at solution points or to what extent deterioration will be allowed.

The TS approach has many suitable basic components within metaheuristic algorithms for solving VRP. There are four basic components: neighborhood search, frequency-based memory, recent memory, and mixed memory structure. The neighborhood search movement, which defines the transition from one solution point to another, is the most basic solution strategy of the TS algorithm. There are various strategies used to increase the solution efficiency of the TS algorithm. The most frequently used activity strategies in the literature have been identified as: aspiration, diversification, intensification, oscillation, and restart.

In the TS algorithm, the solution starts with x_1 and moves to t with each iteration. The movement from X_t to the best neighbor $x_{(t+1)}$ is continued until the stopping criterion is met. The function continues without paying attention to whether $f(x_{t+1})$ is less than f (x_t), where the function f(x) is the cost of x. In order to produce a solution loop in the algorithm, previously examined operations are prohibited. Instead of solution values, only prohibited solutions are recorded in memory to reduce memory and time requirements. Here, short or long-term memory will be preferred depending on the timing of the movements made in the solution space. For this reason, the algorithm must have a memory structure. This memory is examined according to four basic principles: whether the solution has been examined recently, the frequency of review of the solution, the effectiveness of the solution, and the quality of the solution. The TS approach is a solution algorithm that can implement different types of problems by expressing them qualitatively and symbolically without the need for mathematical formulations (Glower & Laguna, 1997:1).

The basic procedures for using TS for optimization are as follows:

Step 1. Determining the initial solution and recording the solution in the appropriate memory as the best available solution.

Step 2. Determining a replacement function according to the neighborhood relationship status of the current solution and performing a neighborhood search.

- Among the non-forbidden solutions, the solution that will optimize the objective function is selected as the new best solution,
- Short, medium, and-long term memory is updated when switching to a new solution,
- If the newly obtained solution is the best solution found, it is recorded as the current best solution.

Step 3. Step 2 is repeated until the specified stopping criterion of the algorithm is met. When the stopping criterion is met, the problem is solved.

The basic solution stages of the TS approach for optimization are expressed in Figure 5 below.

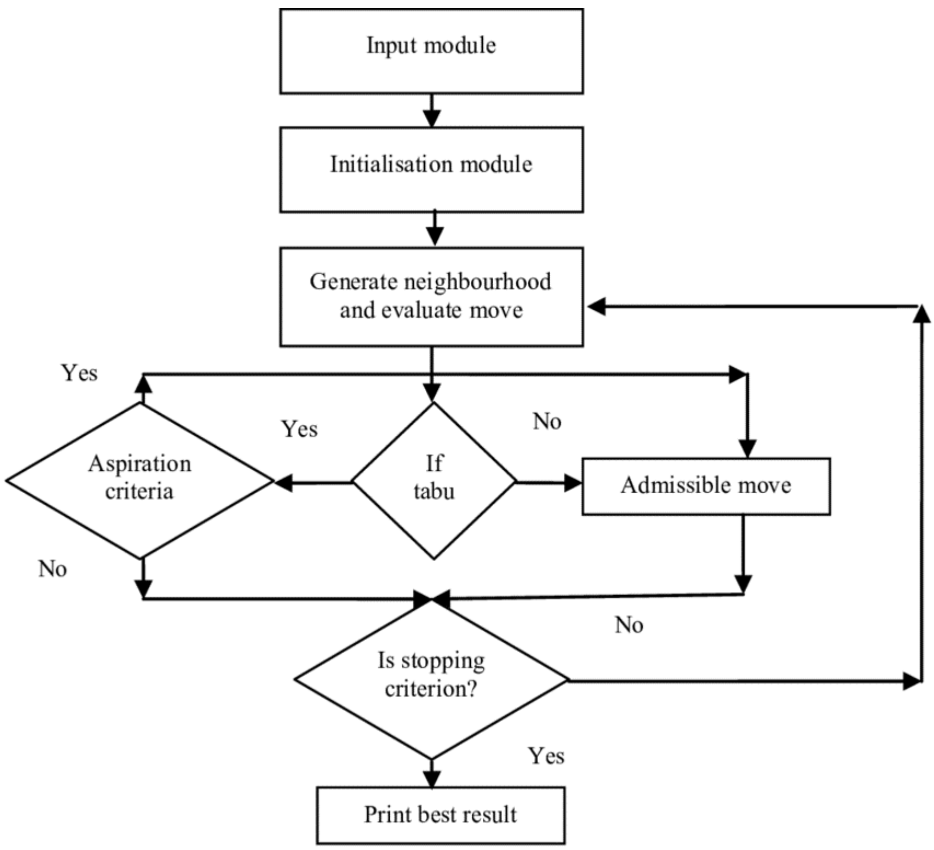

Figure 8. Taboo Search Algorithm Solution Stages

Step 1: The initial solution for the problem is obtained randomly. However, an initial solution can also be obtained by using a heuristic algorithm developed to suit the problem. In this study, it was ensured that the first society consisted of more successful individuals without breaking away from the random denominator through local search support. For this purpose, while placing business chromosomes with permutation coding, local search support is provided by random selection among the individuals closest to it.

Step 2: The TS algorithm has a memory structure in which the solutions produced during the run time or cycle are dynamically stored. While the information in this prohibited list is stored in order to produce a new solution, a new solution that does not stick to a local point in the solution space is allowed, even if it is worse than the current one. This is called the aspiration strategy. According to this criterion which was employed in this study, the banned list was fashioned in this way so that the algorithm can produce new solutions without entering a vicious circle.

The algorithm fitness value is calculated by the scores of the fitness function received from individuals in the current community. Individuals who make the highest contribution to the best solution are taken into account for the fitness value. The suitability value taken into consideration in this study is the time spent in the warehouse for loading, traveling, and unloading according to the company's lists of individuals. This process is carried out sequentially for each vehicle; when the load capacity is exceeded, the selection stops and the next vehicle is moved.

Step 3: The process continues until the stopping criteria for the TS algorithm are met. These criteria vary depending on the problem type, purpose, and volume. Accordingly, the criteria obtained from the basic information in the literature are:

- Reaching a specified number of iterations,
- Non-existence of neighbors of a selected neighboring solution point,
- Achieving a targeted solution value,
- The algorithm gets stuck at some point and cannot produce a better solution.

Approaching the targeted solution value and reaching a specified number of iterations were chosen as stopping criteria for the algorithm in this study. This selection was made based on the basic structure of VRP problems and information obtained from the literature.

4. Results

Within the scope of the application, the distribution operation was optimized for the data set which contains two business days' order information from the Adana central warehouse of Ekol Logistics Inc. The company does not use any mathematical algorithms in its current distribution processes. Transactions are organized in an order determined by intuitive experiences, with the results obtained in practice being compared with this current situation.

For the analysis of the mathematical model produced for CHFGVRP optimization, the GA and TS solution algorithms were run with the help of the C# programming language. The obtained results were evaluated comparatively. For both approaches, the analysis results obtained were examined according to the number of generations determined as the algorithm stopping criterion and their closeness to the targeted solution value. The effectiveness of the algorithm was increased by dividing the businesses in the problem definition into distribution clusters according to their proximity of 100 and 250 meters to each other.

The GA solution results improved as the number of generations increased. This shows that the algorithm works dynamically and effectively according to the solution strategy. In addition, the solution time of the algorithm did not increase very much in parallel with the increase in the number of generations, between 00:05 and 01:52 for both order sets. These two criteria proved that the algorithm was produced with parameters suitable to solve the problem.

Table 3 below expresses the results obtained from order sets with the GA approach. According to the literature, values ranging from 30 to 200 are taken for the number of generations. Due to the large number of order quantities and order points used in this study, the problem structure with high combinations showed that between 50 and 1000 generations were required. The crossover and mutation rates were taken as 0.9 and 0.03, which are generally accepted in the literature. Likewise, the number of crossover type double tournaments and individuals was taken as 250. Weobserved the solution time of the algorithm to be between 00:05 and 01:50 for order set-1 and between 00:06 and 01:52 for order set-2, which means that results are given in an acceptable time.

Figure 9 shows the change in emission amounts according to the number of generations for the two order sets.

Although there is no significant difference in the number of order points between the order sets, the difference in order quantities is significant. This situation will affect the total load amount, that is, vehicle capacity usage, and may increase the overall emissions. However, for both orders, the decreasing trend in emissions that occurred with the generation increase was found to be at similar levels and in very close amounts. This indicates that the algorithm uses vehicle capacities effectively, with distribution to order points being carried out with effective routing. In addition, as the number of generations increased, the effectiveness of reducing the emissions began to decrease. In this way, the limitations of the solution efficiency of the algorithm are revealed.

Table 3. *Genetic Algorithm Solution Results*

		Order Set - 1					Order Set - 2				
Number of Generations	Clustering Distance	Number of Locations	Solution Time	Distance (Km)	Fuel (Lt)	Emission (Gr)	Number of Locations	Solution Time	Distance (Km)	Fuel (Lt)	Emission (Gr)
50	100	100	00:05	3279	529,54	1414428	110	00:06	3105	501,08	1338411
	250	87	00:05	3063	480,03	1282186	95	00:06	2935	591,24	1579202
100	100	100	00:11	3058	536,24	1432323	110	00:13	3030	526,62	1406602
	250	87	00:11	2806	475,68	1270567	95	00:13	2621	449,56	1200801
150	100	100	00:13	2634	471,09	1258308	110	00:15	2492	349,81	934369
	250	87	00:13	2398	380,52	1016395	95	00:15	2682	449,89	1201682
200	100	100	00:15	2619	59,628	1059267	110	00:17	2320	411,52	1099196
	250	87	00:15	2266	354,31	946388	95	00:17	2233	396,45	1058944
250	100	100	00:18	1992	332,30	887600	110	00:21	2186	369,64	987325
	250	87	00:18	2324	408,92	1092252	95	00:21	2099	339,12	905816
300	100	100	00:22	2060	334,28	892888	110	00:24	2282	429,62	1147515
	250	87	00:23	2181	359,39	959957	95	00:26	2177	379,77	1014392
400	100	100	00:28	1788	342,62	915164	110	00:29	2072	343,05	916313
	250	87	00:29	1980	324,03	865510	95	00:30	1937	327,75	875430
500	100	100	00:41	2194	370,63	989978	110	00:44	2169	382,52	1021737
	250	87	00:43	1927	335,12	895132	95	00:46	2075	384	1025664
700	100	100	01:10	1789	332,31	887624	110	01:17	2156	367,73	982233
	250	87	01:13	1827	323,26	863454	95	01:19	2030	359,58	960461
1000	100	100	01:45	1937	333,18	889926	110	01:56	1906	326,90	873167
	250	87	01:50	1741	302,68	808484	95	01:52	1904	325,70	869971

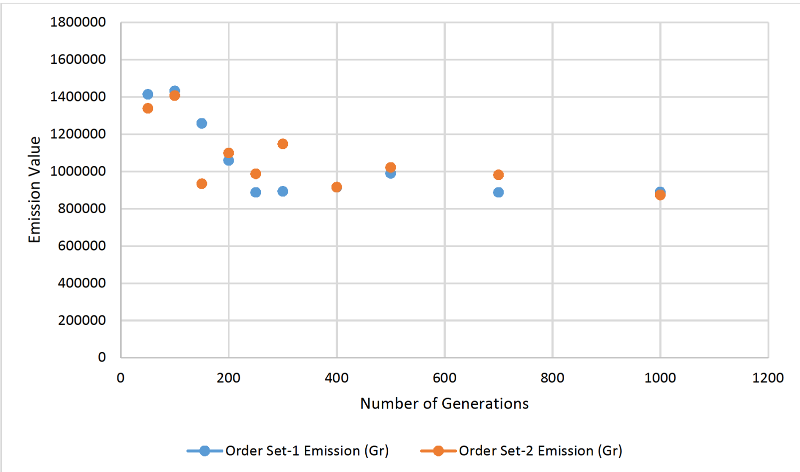

Figure 9. Changes to the Genetic Algorithm Emission Values

The TS solution results for both order sets are expressed in Table 4 below. As with the GA approach, the number of generations was chosen to be between 50 and 1000, in accordance with the problem structure. Solution values were obtained for clustering distances of between 100 and 250 meters for both order cluster customer locations where distribution operations will be carried out. The number of individuals was taken as 250.

In the TS algorithm, the performance of solution times increased with a low acceleration compared to the increase in the number of generations. This result indicates that the produced algorithm has a correct memory structure, local search support supports the solution capacity of the algorithm, and the algorithm works harmoniously with the mathematical model made for the problem. Therefore, as the clustering distance and number of generations increased, the algorithm's resolution speed increased slightly, ranging from 00:04 to 01:46 for both order sets. Despite this, there was a high level of improvement in the solution results. Figure 10 below illustrates the change in emissions according to the number of generations for the two order sets.

For both order sets, the emissions decreases which correspond to the increase in the number of generations are similar. This is proof that the algorithm works effectively for different numbers of order points and order quantities. Similar to the GA results, increasing the number of generations increased the solution efficiency. However, the decrease in the emissions decreased when the number of generations increased. This situation revealed the solution limitations of the algorithm.

Table 4. *Tabu Search Solution Results*

		Order Set - 1					Order Set - 2				
Number of Generations	Clustering Distance	Number of Locations	Solution Time	Distance (Km)	Fuel (Lt)	Emission (Gr)	Number of Locations	Solution Time	Distance (Km)	Fuel (Lt)	Emission (Gr)
50	100	100	00:04	3598	604,91	1615741	110	00:05	4866	800,34	2137722
	250	87	00:04	3517	627,28	1675491	95	00:05	3368	513,88	1372600
100	100	100	00:09	3463	585,60	1564164	110	00:12	3008	448,59	1198210
	250	87	00:10	3216	552,06	1474578	95	00:12	3028	446,72	1193215
150	100	100	00:12	3535	668,68	1786070	110	00:14	2869	424,83	1134747
	250	87	00:13	2681	444,12	1186271	95	00:14	2499	463,67	1238489
200	100	100	00:14	2558	458,24	1223985	110	00:16	2346	377,77	1009050
	250	87	00:15	2273	404,79	1081220	95	00:17	2240	484,48	1294046
250	100	100	00:17	2233	378,62	1011294	110	00:20	2135	344,74	920827
	250	87	00:18	2146	363,82	971789	95	00:21	2260	492,41	1315253
300	100	100	00:20	2258	354,97	948151	110	00:23	2124	392,62	1048714
	250	87	00:21	2117	364,74	974245	95	00:25	2109	457,12	1220994
400	100	100	00:25	2211	422,59	1128764	110	00:27	2037	373,58	997858
	250	87	00:26	2050	387,17	1034157	95	00:29	1878	339,53	906911
500	100	100	00:38	1912	321,06	857577	110	00:41	2007	419,79	1121259
	250	87	00:39	1884	314,36	839682	95	00:42	1827	327,35	874378
700	100	100	01:01	1904	330,83	883673	110	01:10	1975	360,59	963162
	250	87	01:03	1821	331,96	886689	95	01:12	1999	365,60	976544
1000	100	100	01:32	1793	334,99	894784	110	01:44	1951	332,62	888428
	250	87	01:31	1749	311,33	831589	95	01:46	1906	326,12	871093

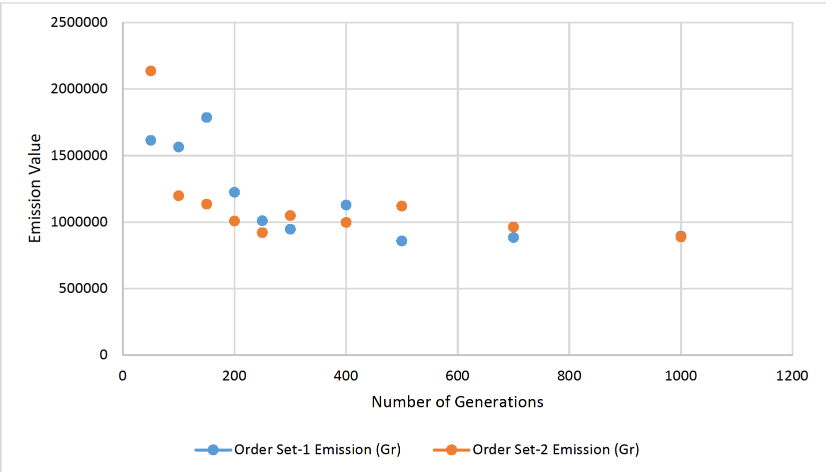

Figure 10. Changes in Emission Values for the Taboo Search Algorithm

The algorithms of both methods used in problem solving and the proposed mathematical model provided strong results with high compatibility in acceptable times. According to the results obtained, it was determined that the GA and TS approaches result in very similar solutions for both order sets. This shows the effectiveness of the algorithms and method selection that work in high harmony with the mathematical model of the problem. In addition, the algorithm parameters and solution strategies determined for both methods resulted in high performance. Table 5 below expresses the comparison of the performance averages of the GA and TS algorithms obtained for both order sets and the distribution operation data intuitively applied by the business.

According to the solution results, the current solution improvement for order set-1 was over 20% on average in both methods. Although there is no significant difference between the healing power of the methods, the GA approach gave better results. For order set-2, the improvement was over 10% on average. Again, there is no significant difference between the methods, but GA is still more effective. The main reason for this difference between the two order sets is that the customer points within the order set are located at very far and dispersed distances for order set-2. This situation affected the algorithm performance, resulting in lower levels of improvement.

Table 5. *Comparison of GA, TS, and Business Existing Solution Results*

Order Set - 1						
Solution Approach	Distance (Km)	%	Fuel (Lt)	%	Emission (Gr)	%
Existing Solution	2241	*	413,97	*	1105713	*
GA	1741	22,3	302,68	26,8	808484	26,8
TS	1749	21,9	311,33	24,7	831589	24,7
Order Set - 2						
Solution Approach	Distance (Km)	%	Fuel (Lt)	%	Emission (Gr)	%
Existing Solution	2197	*	389,13	*	1039366	*
GA	1904	13,3	325,7	16,3	869971	16,2
TS	1906	13,2	326,12	16,1	871093	16,1

5. Conclusion

Planning distribution operations, which are among the logistics management activities, at low costs and with minimal damage to the natural ecological balance is extremely important for the sustainability of social and economic life. This study discusses the green vehicle routing problem with capacity-constrained and heterogeneous fleets, which is a type of green vehicle routing approach that has started to appear frequently in the literature in recent years. The problem was modeled for the optimization of the distribution of a large-scale logistics company operating in Turkey.

In the model developed to solve the problem, a multi-purpose linear model was produced with the objective functions of reducing the amount of fuel and emissions. The study aimed to increase the solution efficiency with the help of two different objective functions. Two different metaheuristic solution approaches were used to solve the problem in the NP-Hard class. The aim here was to compare the solution power of an alternative solution method and the mathematical model used in practice. Both solution methods had close solution efficiency for two different order sets. This indicates that the algorithms are effectively determined with parameters appropriate to the problem structure.

There are many different studies in the literature regarding the green constrained vehicle routing problem. Studies have frequently measured the analysis effectiveness of mathematical models proposed under certain purposes and constraints. For this purpose, some experimental analyses were preferred instead of real business data. This study will contribute to the literature as a result of the real business data used and the analysis applied comparatively with two different metaheuristic approaches. In future studies, more dynamic models and solution algorithms can be produced by adding such constraints as traffic density, load weight, and road slope to real-life problems.

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ORCID:

Furkan Dişkaya 0000-0001-9581-6771
Sait Erdal Dinçer 0000-0002-8310-1418

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