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Evaluation of a bi-objective vehicle routing problem considering time constraints

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Abstract

In today's competitive market, reducing costs and time is one of the most important issues that has occupied the minds of managers and researchers. This issue is especially important in the field of supply chain management and transportation because by reducing time and cost, manufacturers and service providers can gain a competitive advantage over competitors. Accordingly, vehicle routing issues are one of the most important issues in this field because it is directly related to the time of service or product delivery and also by optimizing the network, reduces the cost of the entire network. Therefore, in this study, the intention was to evaluate the problem of vehicle routing (trucks) by considering the time constraints and using a multi-objective approach. Therefore, we discussed each of the factors separately based on the issue. The results of this study show. In this research, the model with two objective functions will be solved by two metaheuristic algorithms NSGA-II and MOPSO Managers are concerned with time and cost management in today's competitive markets, which is seen as a source of competitive advantage. The present study aims to find a solution to a bi-objective function model by employing two metaheuristic algorithms, NSGA-II and MOPSO. Additionally, a criterion for comparing algorithms is presented. The findings show that the MOPSO algorithm yields the optimal solution. The contribution of the present study in comparison with other previous studies can be summarized as follows: Environmental protection based on reducing pollution and its effects as well as reducing costs. Finding the desired route taking into account the complexity and difficulty of the route. Managers are concerned with time and cost management in today's competitive markets, which is seen as a source of competitive advantage. The present study aims to find a solution to a bi-objective function model by employing two metaheuristic algorithms, NSGA-II and MOPSO. Additionally, a criterion for comparing algorithms is presented. The findings show that the MOPSO algorithm yields the optimal solution. The contribution of the present study compared to other previous studies can be environmental protection and cost reduction that the two factors are compared and the results of the two methods are analyzed.

Keywords: exchange locations; vehicle routing problem; NSGA-II and MOPSO vehicle routing problem; time constraints.

Paper Type: Original Research

1. Introduction

Supply chain management is a method for lowering the final price while improving the speed and quality of services to achieve a competitive advantage. Additionally, it is necessary to reduce environmental contamination. A supply chain is based on focusing on commercial concerns, rather than on the economic and environmental challenges facing businesses (Roy et al., 2018). Additionally, non-compliance with ethical standards and responsibilities will increase business costs and reduce profitability (Saberi et al., 2018). Optimization problems can be classified into two types: single-objective and multi-objective. The single-objective optimization aims to improve a single performance index whose minimum or maximum value accurately reflects the quality of the response obtained. However, in some cases, it is impossible to score a hypothetical solution to the optimization problem solely based on one index. We will discuss each of the factors individually considering the related problem. The first and most critical issue that should be addressed is the polluting gas emissions caused by worn and old vehicles, low-quality fuels, a lack of standards and pollution control tests, and so on, which can be controlled by managing the type of fuel and the use of low-consumption and efficient trucks. As a result, it can be concluded that pollution reduction is a critical and necessary objective that should be considered in the current study. To develop an initial solution, Chao (2002) proposed a two-phase method. The tabu search employed in the two methods examines neighborhood structures based on the standard VRP movement as well as the so-called subnet root refinement movement (including full sub-tour connection to a different train passenger.) Lin et al. (2009) proposed an exploratory method that uses simulated annealing to improve an initial solution. To find the initial solution, they used the route-first, cluster-second approach. Villegas et al. (2011) also used the first-route, cluster-second method based on route to find a solution. More specifically, they used the route-first, cluster-second method in the greedy randomized adaptive search procedure (GRASP). Karamia and Guerriero (2010) proposed

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an approach based on mathematical programming and local search to find a solution. In 2012, Derrigs et al. proposed an exploratory approach that combines local search with large neighborhood search. Villegas et al. (2013) proposed a hybrid method that combines GRASP and iterated local search (ILS) based on mathematical scheduling. The truck and trailer routing problem (TTRP) has developed into several types: multi-warehouse, multi-period TTRP (Lazić J and 2014), slow TTRP where limited fleet constraints have been reduced (Lin SW, Yu VF, Chou S-Y and 2010), RTTRP with time window (Chou S-Y et al. 2010), TTRP without load transfer and TTRP with time window (Derigs U, Pullmann M, Vogel U and 2013) TTRP with a time window, site dependence and heterogeneous fleet (Bederina, H et al. 2018), etc.
Therefore, a mathematical bi-objective mixed linear programming model was proposed. The first objective function is to determine strategies for minimizing total costs including truck costs, vehicle maintenance costs, and transportation costs. The second objective is to protect the environment and nature by minimizing pollution associated with fossil fuel consumption and vehicle traffic for all purposes. TTRP is a subset of Chao's vehicle routing problem (Chao, 2002). The first dimension includes financial and economic factors which can be classified into four categories: strategic factors (such as cost reduction), maintaining superior financial performance, tactical factors (such as costs), and operational factors (cycle time, customer returns, and energy consumption) (Presley et al., 2007). The second dimension (environmental dimension) is the emergence of the concept of green supply chain management as a result of the increase in environmental issues and various pollutants associated with the development of industries. We will solve the mathematical model using two meta-heuristic algorithms, NSGA-II and MOPSO, and will determine which of these two algorithms performs better at solving the problem. To accomplish this, 100 problems were generated in three categories: small, medium, and large, based on the number of train passengers, truck passengers, and exchange locations. After defining the dimensions of the generated problems, we will discuss the results obtained using the NSGA-II and MOPSO meta-heuristic algorithms, followed by an analysis of the results. The bi-objective TTRP will be considered in this research to minimize costs and pollution. Green supply chain management has been increasingly employed in business approaches and research over the past years because of the rapid erosion of natural resources. It is an important issue for companies that incorporate economic and environmental issues in their strategy. Also, considering environmental issues in any organization is not possible without supply chain management. Supply chain management is defined as the management of the flow of materials and information if the objectives of all dimensions, namely economic and environmental, are considered (Govindan et al., 2013). The present study examines TTRP, which is a generalization of VRP (vehicle routing problem). The main differences between this research and VRP are: The vehicle fleet consists of a truck, a semi-trailer, and a swap body.
In general, this problem occurs in cases where due to some limitations, the passengers of a truck-trailer combination may not be available. The real applications of this problem for the dairy industry are presented in Hoff A, 2006 (Gerdessen JC, 1996). Chao (2002) and Scheuerer (2006) proposed exploratory methods based on tabu search. In both methods, first, a practical initial solution was formulated and then was enhanced by a tabu search.The present study examines the bi-objective TTRP, the objectives are minimizing costs and pollution. The innovations of this research include the integration of macro decisions, the consideration of dual objectives, and the integrated study of minimizing operating costs and reducing greenhouse gas emissions as an indicator of pollution. In general, it is possible to simultaneously study a bi-objective model with specific features, and employ optimization methods and meta-heuristic algorithms to solve and validate the design model in this study. The model with basic assumptions as well as cost parameters and prevailing environmental indicators can be integrated to optimize the objectives and determine the number and location of customers and transportation planning between different routes. Therefore, the first part of the study includes an introduction. The second part is the review of the related literature. Problem-solving methods are discussed in the third part of the study. The fourth part includes data analysis and discussion, and the final section includes the conclusion and suggested topics for future research.This method provides a mechanism for network reconstruction in which the distribution network is attacked and each of its nodes or arcs is stopped. It is very difficult to find a solution to VRP. In this way, by reconstructing the route and the cost matrix, possible solutions can be obtained (2021, Gabriel-Policroniades). Regarding the complexity of the problem, solving large problems using precise methods is a very time-consuming task. Therefore, a multidisciplinary meta-exploration method based on simulated cooking has been developed (YannisAncele et al. 2021a).
The contribution of the present study in comparison with previous studies can be summarized as follows:

- Environmental protection based on reducing pollution and its effects as well as reducing costs.
- Finding the desired route considering the complexity and difficulty of the route.
- Examining the two factors simultaneously and comparing the results of two meta-heuristic methods.

2. Literature review

In VRP each customer must be assigned exactly to a vehicle. Total customer demand on the same route must be less than or equal to the capacity of the vehicle. The classic goal is to minimize the cost of the entire route (Toth and Vigo, 2002). However, some functions minimize the total distance traveled, total travel time, or total cost.

The capacitated vehicle routing problem (CVRP) is a real-life problem that one or more elements of which are unknown. To model the CVRP, some of the parameters in the general formula are usually displayed randomly. By inserting random data in the problem, we can have the stochastic (capacitated) vehicle routing problem (SVRP or SCVRP) (Gendreau et al. 2014). Gendreau et al. 2014 have thoroughly reviewed the early literature on SVRP and provided a brief description of the relevant concepts and solutions. Laporte et al. (2002) examined the capacitated vehicle routing problem with stochastic demands (CVRPSD) and considered two types of theoretical demand distributions: Poisson and Normal. Computational tests were performed on both distributions (Laporte et al., 2002). The same problem is found in Jabali et al. (2014) where claims are theoretically treated independently and evenly distributed. However, the tests are conducted using the normal distribution (Jabali et al., 2014).
Mendoza et al. (2010, 2011), studied the capacitated vehicle routing problem with potential demand (CVRPPD). Goodson (2015), addresses a similar problem, where each route is subject to the travel time limit. A method is proposed to calculate the expected cost of the solutions. However, this method only works with discrete distribution (Goodson 2015). Due to this limitation, Mendoza et al used a different method, and the available results were compared to the assumption of demand with normal distribution.The problem is solved using generalized algebraic modeling system software in small-size problems. The problem is NP-hard and requires an efficient solution methodology. For this purpose, a hybrid algorithm has been proposed to solve large-size problems. The efficiency of this algorithm is checked by making comparisons with exact solutions for small and medium-size test problems, and with the related literature for large size problems (Ashkan Ayough, Reza Rafiei, and Ashkan Shabbak 2020).The capacitated vehicle routing problem with the possible travel time has also been studied. Travel time is considered an element that stimulates CVRP. A version of CVRP with a soft time window and random travel time was studied (Ando, 2006). In this model, a vehicle is allowed to travel several routes daily and all goods of each customer must be loaded on the vehicle at the same time. The total weight of the goods on one route should not exceed the capacity of the vehicle. In addition, there is a hard time window for storage. The triangular distribution for travel time is estimated using real data. This problem aims to minimize the total cost, which includes the fixed cost of using the vehicles, operating costs, and fines for leaving the time windows. Late/early entry fines can be selected as a return. It is assumed that the service time is fixed.
Both methods are developed for the first time and the initial solution is improved by the tabu search. To find an initial solution, Scheuerer (2006) proposed a two-step method that, in the first phase, simplifies the allocation problem to assign customers to routes. Then, a meta-heuristic method is developed and used. The routes generated by Scheuerer (2006), on the other hand, used two clustering methods for routing, called T-Sweep and T-Cluster, to create an initial solution. The tabu search used in these two approaches has standardized traditional structures based on VRP. Lin et al. (2009), proposed an exploratory approach to generate the initial solution of a simulated loop for improvement. They used a method based on the cluster-first cluster-second approach to solving a truck and trailer routing problem. Also, Guerriero and Caramia (2010), proposed a method to solve VRP based on mathematical planning and neighborhood search.A mathematical method was used to model and solve the problems of customer routing and assigning the customer to the route. A model with a mathematical planning framework that has been continuously solved on the following theme: the customer route allocation problem, which seeks to minimize the fleet used to serve customers, and the route definition problem, which seeks to minimize the total distance according to a set of customers assigned to each vehicle (Derigs et al. 2013)
Another exploratory approach to VRP includes local search and large neighborhood search. This exploratory method examines not only the neighbors of the classical vehicle routing problem but also the specific neighbors for the vehicle routing problem. The main advantage of this exploratory approach is that it can easily be used to deal with different types of vehicle routing problems. Allahviranloo et al. (2014), proposed three new formulas to provide different optimization solutions reliable, robust, and fuzzy selective routing problems solved using three different types of genetic algorithms.Zhang et al. (2015), presented a VRP regarding fuel consumption and carbon emissions, which has been solved by the meta-heuristic method of the extended tabu search algorithm. Lin et al. (2016), designed a multi-objective model to find an optimal routing strategy to minimize travel time and energy costs. Vincent et al. (2016), proposed a vehicle routing model with a crossover dock that reduces costs and time. They have also developed a Simulated Annealing to solve the model. Todosijević et al. (2017a), proposed two methods of integrated neighborhood variable search to solve the problem of reducing the cost of vehicle routing. Rodríguez-Martín et al. (2018), proposed an integer linear programming model to minimize the vehicle traveling costs as well as a branch-and-cut algorithm to solve the problem. Gutierrez et al. (2018), developed a combined methodology consisting of a Memetic algorithm and random privacy search method to solve the vehicle routing problem with potential demand. Toffolo et al. (2018), proposed a model for the Swap-Body vehicle routing problem (SB-VRP) to reduce service costs and time. Also, the same paper provides a possible local search method for solving and obtaining answers. A time window is associated with each server, and some services require simultaneous visits to several different vehicles. This study seeks to reduce service times. Bederina & Hifi (2018), optimized and solved the stable hybrid multi-objective model to reduce the number of vehicles and travel costs by using a hybrid meta-innovation algorithm and local operators. The literature related to the research topic is summarized in Table 1:

Table 1: Research literature

Reference	Year	Number of Objectives			Objectives	Modeling method	Solution	Field	
		Single-objective	Bi-objective	Multi-objective				Economic	environmental
Brandstätter and Reimann	2018	*			Reduce total costs	Exact	Linkage and Split methods	*	*
Bula et al.	2018		*		Reduce total costs Reduce total routing risks	Exact	ε-constraint method Dominance-based neighborhood algorithm	*	*
Domínguez-Martín et al.	2018	*			Reduce driver costs	Exact	Branch-and-cut algorithm	*	-
Fernández et al.	2018	*			Reduce total operating costs	Exact	Branch-and-cut algorithm	*	-
Li et al	2018	*			reduce fuel consumption and carbon emissions	Exact	Adaptive tabu search	*	*
Matos et al.	2018	*			Reduce routing costs	Exact	CPLEX C++	*	-
Ostermeier and Hübner	2018	*			Cost reduction	Exact	Large neighborhood search	*	-
Zhang et al.	2018	*			Reduce the energy consumption of electric vehicles	Exact	Ant colony algorithm	*	*
Li et al.	2019		*		Reduce costs and time and emissions	Exact	Ant colony algorithm	*	*
Goudarzi et al.	2020		*		Reduce total operating costs and maximize early and delay	Exact	Pareto genetic algorithm	*	-
Present study	2021			*	Reduce total costs Reduction of environmental	metaheuristic	Heuristic and meta-heuristic methods	*	*

According to Table 1, the studies show that research in this field is mainly green single-objective or economic rather than two green objectives. So far, a green bi-objective study has not been conducted, so the present study can be considered as the first bi-objective research. On the other hand, the objectives and environment under study focused only on reducing total costs or incidental costs in the economic or green environment, but the above research aims to reduce total costs and environmental pollution while increasing and also the desirability of the route based on combined methods., unlike the previous studies, the present paper will examine the economic and environmental aspects of enclosed and flatbed trailers at the same time. Therefore, in summary, the innovations of the present study compared to other previous studies are:

- Find a set of routes that help minimize costs
- Protect the environment by reducing pollution and its effects as well as reducing costs

3. Research methods

To gradually face the complexity of the proposed topic in the stages of research, it is better to break the research into several stages and increase its complexity in each stage to deal with the complexities of the research in a structured way, and to use the results of each stage in the next stage. In this regard, first, an optimization model for the closed-loop supply chain, in which the manufactured products are sent directly from the manufacturers to the customers, is presented. Then, in the next problem, the transit warehouse is used as a combined facility that acts as a transit warehouse in direct flow and as a collection center in reverse flow. Also, the possibility of outsourcing transportation and third-party logistics providers will be considered. In the third problem, the discussion of vehicle routing with the assumption of soft time windows is included in the model, and finally, considering the effect of returned products on the customer ordering pattern and the waiting time for reviving returned products through a queueing model, the problem will be rewritten. In all the problems, the objective functions are presented as minimizing the total costs and the total operating time of the chain. To solve the developed dels, if possible, nonlinear programming models are converted into linear models and accurate methods of solving linear problems are used. Otherwise, the use of heuristic or meta-heuristic algorithms to solve the models will be considered. The key issue in vehicle routing is the management of a fleet of vehicles that provide delivery or collection services, or a combination of the two, to a set of customers. In addition to deciding on the number and type of vehicles, the planning manager must also specify by what means and in what order customers are tracked to reduce shipping costs. Therefore, researchers are trying to provide methods that reduce the cost of transportation in this system. The problem of truck and trailer routing is introduced in 2002 by Chao. It includes trucks and trailers and a set of customers receiving service (Chao, 2002). Every truck/trailer has a capacity limit and every customer has a demand that must be met using the existing fleet. Not all customers are permitted to be serviced by a truck trailer, so there are two types of customers: train customers who can be serviced by a truck that tows a trailer or truck alone, and truck customers who can only be serviced by a single truck. The truck can start the route from the warehouse or without a trailer attached. Switching trailers between trucks on the route is not allowed, in other words, if a truck leaves the warehouse with a trailer attached, it must return to the warehouse with the trailer attached. Also, exchanging the load between the truck and the trailer on the route is permitted.

3.1. Solving and validation of the proposed model

During the modeling process, the model maker must make sure that the designed model includes all the necessary components of the system and runs well. In fact, in modeling, we want the model to be implemented as we intended it to be. This process is known as checking the validation of the model and is a continuous process during modeling. For this purpose, in the following, we will examine the validation of the model using the GAMS optimization software.
To solve the problem using GAMS software, due to the multi-objective nature of the problem, the Epsilon constraint method has been used. In the following, we first solve an example with GAMS software and using the e-Constraint method, and then present the results.

3.2. Epsilon constraint method (e-constraint)

The Epsilon constraint method is one of the well-known approaches to dealing with multi-objective problems. It solves this type of problem by transferring all but one of the objective functions to the constraint at each stage (Ehrgott & Gandibleux, 2002). The Pareto boundary can be created by the e-constraint method (Berube et al., 2009).

$$\min f_1(x)$$

$$f_2(x) \le \varepsilon_2$$

$$\dots$$

$$f_n(x) \le \varepsilon_n$$

$$x \in X$$

The steps of the e-constraint method are as follows:

- Select one of the objective functions as the main objective function.
- Solve the problem each time according to one of the objective functions T and obtain the optimal values of each objective function.
- Divide the interval between the two optimal values of the sub-objective functions into a predetermined number and obtain a table of values for e2…, en.
- Solve the problem each time with the main objective function with any of the values between e2…, en.
- Report the Pareto optimal solutions found.

3.3. Conclusions on model validation

As the figure shows, an increase in the first objective function has caused an increase in the second objective function which is directly related to the fact that an increase in the costs of transportation and travel, also increases energy and fuel consumption, which in turn increase pollution. By reducing the value of the objective function, the costs and pollution will be reduced. The following is the result of solving a numerical example by the Epsilon method in Figure 3. This figure shows how the values of the objective functions affect each other. This figure shows the results obtained from the Epsilon method in ten intervals. According to this figure, with the increase of the total cost, the amount of pollution in the system has increased. The Swap-Body Vehicle Routing Problem (SB-VRP) is a type of VRP proposed by the Automotive Logistics Working Group and a German company. To solve the SB-VRP, meta-heuristic methods have been used. In this case, there are an unlimited number of vehicles in stock, including trucks, trailers, and swap bodies. Only the swap body can be loaded, but the loads should not exceed the vehicle's maximum capacity. Among the existing fleet in this problem, only two combinations of vehicles are allowed: 1) a truck carrying a swap body, 2) a truck and a trailer (called a train) that has two swap bodies. Using the existing combinations of vehicles, a set of customers must be serviced exactly once during the service, i.e., the route that starts and ends in the warehouse. The time required to provide the service as well as the restrictions on access to that service must also be considered. This means that some customers (called truck customers) can only be visited by truck, while other customers may be visited by train. However, even if the two-body train leaves the warehouse, it can return to the truck customers after detaching the hull at designated locations called swap locations. If a trailer is detached from the truck at the swap location, it must be reattached by the same truck before returning to the warehouse. A truck/train must return to the warehouse with the same swaps with which it left. The following four actions are permitted in the swap locations:

1. A truck parks a trailer at a swap location and continues its way with only one body. (Park)
2. A truck picks up a trailer that was previously parked at the swap place and continues its way (Pick Up)
3. A truck parks the swap body that is currently being transported and picks up another body that is parked at the swap place and continues its way (Swap).
4. A truck parks a trailer then parks the swap body between a truck and a trailer and continues its way. Exchanging the cargo between swap bodies is not allowed, either in the swap locations or in the sites of customers, even if it belongs to the same train. However, if the customer is visited by train, their demand may be exchanged on two bodies (Exchange).

In other words, SB-VRP is a type of vehicle routing problem that has been well studied and includes other complex factors that are observed in practice. In this case, a homogeneous fleet of an unlimited number of trucks, semi-trailers, and swap bodies is used to serve the customer body. Due to a set of location restrictions, some customers may be served by trucks. Four types of operations (parking, loading, exchange, and swap) can be performed at designated swap locations, each of which has an associated time cost. An overview of the vehicle used is shown in Figure 1.

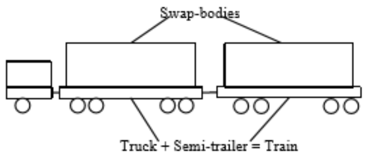

Figure 1: Overview of the vehicle used

Each sub-tour includes truck or train customers, while the main tour only includes train customers (if any) and swap locations. Having a one-way travel sub-tour means that a train visits a swap place and makes some exchanges (park or exchange) to a group of customers (truck customers or train) and then returns to the last swap location and performs the exchange operation again (pick-up or swap). In the case that the pick-up operation occurs at the place of exchange, the train moves in the main route (picks up and continues its main route), otherwise, a truck creates more than one side tour in an exchange location. This is shown in Figure 2 (Lum et al, 2015).

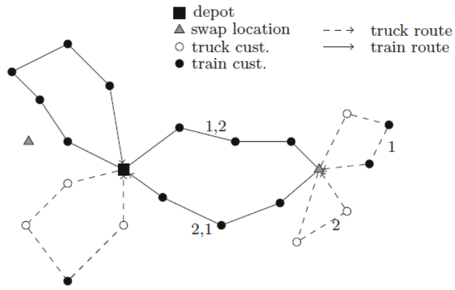

Figure 2: An example of the answer obtained from several sub-tours in one swap location

As described, this problem has been solved with different goals and hypotheses. In this research, we will present the SB-VRP with two objectives. These goals include: 1) Minimizing the total cost of the problem. The cost of the problem includes the cost of using the truck and trailer, the cost of the distance traveled by truck and trailer, the cost of the total travel time, the service time, and the total time spent on the exchange. 2) Minimizing the environmental pollution. In this section, after defining the indices, parameters, and variables of the problem, we will describe the mathematical model of the problem.

D: Depot
C: Set of Customers

L: Set of exchange locations
N: Set of nodes (N = {D} + C + L)
T: Set of trucks
S: Set of semi-trailers
qi: The number of products to be delivered to the iϵC customer.
pi: If the iϵC customer is visited by train 1, otherwise zero.
Si: iϵC customer service time
D: Set of operations (D = {P, U, W, E}): P (parking), U (loading), W (swapping), and E (exchange).
ρl: The time required to execute the lϵO operation
K: Set of indicators (moments). Each indicator shows the number of node orders in a route
Q: Maximum exchange capacity
tij: The time required to cross node i to j
dij: distance between nodes i and j
C_F^T: Fixed cost of using truck t
C_F^S: Fixed cost of using trailer s
C_D^T: Fixed cost due to distance traveled by truck
C_D^S: Fixed cost due to distance traveled by trailer
C_T: Fixed cost per unit of time spent
$Pull^t$: Pollution caused by using truck t (based on fuel consumption)
$Pull^s$: Pollution caused by using trailer s (based on fuel consumption)
$Dosh_{ijt}^T$: Risk of the route between i and j due to the use of truck t (based on the dispersion of the population on the route)
$Dosh_{ijs}^S$: Risk of the route between i and j due to the use of trailer s (based on the dispersion of the population on the route)
u_t^T: If truck t is used 1, otherwise zero.
u_s^S: If trailer s is used 1, otherwise zero.
a_{st}: If trailer s is attached to truck t.
X_{ikt}^T: If node i is met by truck t on the kth route 1, otherwise zero.
X_{iks}^T: If node i is met on the kth route by trailer s 1, otherwise zero.
Y_{ijt}^T: If from node i to node j is travelled by truck t 1, otherwise zero.
Y_{ijs}^S: If from node i to node j is travelled by trailer s 1, otherwise zero.
q_{kt}^T: The capacity of truck t at the moment k
q_{ks}^S: The capacity of trailer s at the moment k
Z_{ikt}^T: The value delivered at moment k at node i by truck t
Z_{iks}^S: The value delivered at moment k at node i by trailer s
D_{ikst}^l: If node kth on route (iϵL) performed operation l by truck t and trailer s 1, otherwise zero.

This cost is equal to the fixed cost of using the truck plus the fixed cost of using the train on any route. In fact, in general, the cost of using a truck and trailer is calculated by relation a:

$$\sum_{t\epsilon T} C_F^T u_t^T + \sum_{s\epsilon S} C_F^S u_s^S \tag{1}$$

This cost is equal to the fixed cost due to the distance traveled by a truck multiplied by the distance traveled between the two nodes plus the fixed cost due to the distance traveled by a train multiplied by the distance traveled between two nodes. In fact, in general, the costs due to the distance traveled by trucks and trailers are calculated by relation b:

$$\sum_{t\epsilon T}\sum_{i\epsilon N}\sum_{j\epsilon N} C_D^T d_{ij}\, Y_{ijt}^T + \sum_{s\epsilon S}\sum_{i\epsilon N}\sum_{j\epsilon N} C_D^S d_{ij}\, Y_{ijs}^S \tag{2}$$

This cost is equal to the fixed cost associated with moving between two nodes. Indeed, the costs of total travel time are generally calculated using the relation c:

$$C_T \sum_{t\epsilon T}\sum_{i\epsilon N}\sum_{j\epsilon N} t_{ij} Y_{ijt}^T \tag{3}$$

This cost reflects the time required to complete each of the four exchange operations (if any) at a fixed rate per unit of time spent. Indeed, the costs of the total time spent performing the exchange operation are generally calculated using the relation d:

$$C_T \sum_{i\epsilon L}\sum_{k\epsilon K}\sum_{s\epsilon S}\sum_{t\epsilon T}\sum_{l\epsilon O} \rho_l\, D_{ikst}^l \tag{4}$$

The first goal is to investigate cost minimization. These costs include the cost of the truck and trailer itself, the cost of the distance traveled by truck and trailer, the cost of total travel time, service time, and total time spent on exchange operations. Thus, when the above-mentioned costs are added together, we obtain the following:

$$\min Z_1 = \sum_{t\epsilon T} C_F^T u_t^T + \sum_{s\epsilon S} C_F^S u_s^S + \sum_{t\epsilon T}\sum_{i\epsilon N}\sum_{j\epsilon N} C_D^T d_{ij} Y_{ijt}^T + \sum_{s\epsilon S}\sum_{i\epsilon N}\sum_{j\epsilon N} C_D^S d_{ij} Y_{ijs}^S + C_T \sum_{t\epsilon T}\sum_{i\epsilon N}\sum_{j\epsilon N} t_{ij} Y_{ijt}^T + C_T \sum_{i\epsilon N} S_i + C_T \sum_{i\epsilon L}\sum_{k\epsilon K}\sum_{s\epsilon S}\sum_{t\epsilon T}\sum_{l\epsilon O} \rho_l D_{ikst}^l \tag{5}$$

This is the pollution generated by a truck or train traveling between nodes. Indeed, the total amount of pollution generated is generally equal to the relationship f:

$$\min Z_2 = \sum_{s\epsilon S}\sum_{i\epsilon N}\sum_{j\epsilon N} d_{ij}\, Pull^s Y_{ijs}^S + \sum_{t\epsilon T}\sum_{i\epsilon N}\sum_{j\epsilon N} d_{ij}\, Pull^t Y_{ijt}^T \tag{6}$$

S.T.

$$u_s^S \le \sum_{t\epsilon T} a_{st} \quad , \quad s\epsilon S \tag{6-1}$$

$$\sum_{s\epsilon S} a_{st} \le u_t^T \quad , \quad t\epsilon T \tag{6-2}$$

$$\sum_{i\epsilon N} X_{ikt}^T \le u_t^T \quad , \quad t\epsilon T, k\epsilon K \tag{6-3}$$

$$\sum_{i\epsilon N} X_{iks}^S \le u_s^S \quad , \quad s\epsilon S, k\epsilon K \tag{6-4}$$

$$X_{00t}^T = u_t^T \quad , \quad t\epsilon T \ ; \ X_{00s}^S = u_s^S \quad , \quad s\epsilon S \tag{6-5}$$

$$\sum_{k>0} X_{0kt}^T = u_t^T \quad , \quad t\epsilon T; \ \sum_{k>0} X_{0ks}^S = u_s^S \quad , \quad t\epsilon T \tag{6-6}$$

$$\sum_{i\epsilon N} X_{ikt}^T = u_t^T - \sum_{1\le h<k} X_{0ht}^T \quad , \quad t\epsilon T, k\epsilon K \tag{6-7}$$

$$\sum_{i\epsilon N} X_{iks}^S = u_s^S - \sum_{1\le h<k} X_{0hs}^S \quad , \quad s\epsilon S, k\epsilon K \tag{6-8}$$

$$X_{ik+1t}^T + X_{ikt}^T \le 1 \quad , \quad i\epsilon N, t\epsilon T, k\epsilon K, k \le |K| - 1 \tag{6-9}$$

$$X_{ik+1s}^S + X_{iks}^S \le 1 \quad , \quad i\epsilon N - L, s\epsilon S, k\epsilon K, k \le |K| - 1 \tag{6-10}$$

$$\sum_{t\epsilon T}\sum_{k\epsilon K} X_{ikt}^T = 1 \quad , \quad i\epsilon C \tag{6-11}$$

$$Y_{ijs}^S \le Y_{ijt}^T + 1 - a_{st} , \quad i, j\epsilon N, i \ne j, s\epsilon S, t\epsilon T \tag{6-12}$$

$$X_{ikt}^T \le X_{iks}^S + 1 - a_{st} , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T \tag{6-13}$$

$$X_{ikt}^T + a_{st} + X_{ik-1s}^S - 2 \le O_{ikst}^W + O_{ikst}^U \le 4 - X_{ikt}^T - a_{st} - X_{ik-1s}^S , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \ge 1 \tag{6-14}$$

$$X_{ikt}^T + a_{st} + X_{ik-1s}^S - 1 \le O_{ikst}^P + O_{ikst}^E \le 3 - X_{ikt}^T - a_{st} + X_{ik-1s}^S , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \ge 1 \tag{6-15}$$

$$O_{ikst}^P \le X_{ik+1t}^T \quad , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-16}$$

$$O_{ikst}^E \le X_{ik+1s}^S \quad , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-17}$$

$$O_{ikst}^W \le X_{ik+1s}^S \quad , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-18}$$

$$X_{ik+1s}^S \le 1 - O_{ikst}^U \quad , \quad i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-19}$$

$$q_{ks}^S - Q\left(1 - O_{ikst}^E\right) \le q_{k+1t}^T \le q_{ks}^S + Q\left(1 - O_{ikst}^E\right) , i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-20}$$

$$q_{kt}^{T} - Q(1 - O_{ikst}^{E}) \le q_{k+1s}^{S} \le q_{kt}^{T} + Q(1 - O_{ikst}^{E}) \text{ , } i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-21}$$

$$q_{ks}^{S} - Q(1 - O_{ikst}^{W}) \le q_{k+1t}^{T} \le q_{ks}^{S} + Q(1 - O_{ikst}^{W}) \text{ , } i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-22}$$

$$q_{kt}^{T} - Q(1 - O_{ikst}^{W}) \le q_{k+1s}^{S} \le q_{kt}^{T} + Q(1 - O_{ikst}^{W}) \text{ , } i\epsilon L, s\epsilon S, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-23}$$

$$0 \le Z_{ikt}^{T} \le q_i X_{ikt}^{T} \quad , \quad i\epsilon C, k\epsilon K, t\epsilon T \tag{6-24}$$

$$0 \le Z_{iks}^{S} \le q_i X_{iks}^{S} \quad , \quad i\epsilon C, k\epsilon K, s\epsilon S \tag{6-25}$$

$$\sum_{k\epsilon K} \sum_{s\epsilon S} \sum_{t\epsilon T} (Z_{ikt}^{T} + Z_{iks}^{S}) = q_i \quad , \quad i\epsilon C \tag{6-26}$$

$$q_{0t}^{T} \le Q u_t^{T} \quad , t\epsilon T \tag{6-27}$$

$$q_{0s}^{S} \le Q u_s^{S} \quad , s\epsilon S \tag{6-28}$$

$$q_{kt}^{T} - \sum_{i\epsilon C} Z_{ikt}^{T} - Q \sum_{i\epsilon L} \sum_{s\epsilon S} (O_{ikst}^{W} + O_{ikst}^{E}) \le q_{k+1t}^{T} \le q_{kt}^{T} - \sum_{i\epsilon C} Z_{ikt}^{T} + Q \sum_{i\epsilon L} \sum_{s\epsilon S} (O_{ikst}^{W} + O_{ikst}^{E}) \text{ , } k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-29}$$

$$q_{ks}^{S} - \sum_{i\epsilon C} Z_{iks}^{S} - Q \sum_{i\epsilon L} \sum_{t\epsilon T} (O_{ikst}^{W} + O_{ikst}^{E}) \le q_{k+1t}^{T} \le q_{ks}^{S} - \sum_{i\epsilon C} Z_{iks}^{S} + Q \sum_{i\epsilon L} \sum_{t\epsilon T} (O_{ikst}^{W} + O_{ikst}^{E}) \text{ , } k\epsilon K, s\epsilon S, k \le |K| - 1 \tag{6-30}$$

$$X_{iks}^{S} \le p_i \quad , \; i\epsilon C, k\epsilon K, s\epsilon S \tag{6-31}$$

$$X_{ikt}^{T} + X_{ik+1t}^{T} - 1 \le Y_{ijt}^{T} \quad , \quad i, j\epsilon N, k\epsilon K, t\epsilon T, k \le |K| - 1 \tag{6-32}$$

$$X_{iks}^{S} + X_{ik+1s}^{S} - 1 \le Y_{ijs}^{S} \quad , \quad i, j\epsilon N, k\epsilon K, s\epsilon S, k \le |K| - 1 \tag{6-33}$$

$$\sum_{i\epsilon N} \sum_{j\epsilon N} t_{ij} Y_{ijt}^{T} + \sum_{i\epsilon C} \sum_{k\epsilon K} S_i X_{ikt}^{T} + \sum_{i\epsilon L} \sum_{k\epsilon K} \sum_{s\epsilon S} \sum_{l\epsilon O} \rho_l O_{ikst}^{l} + \sum_{i\epsilon N} \sum_{j\epsilon N} \sum_{k\epsilon K} Traf_{ijk}^{T} Y_{ijt}^{T} \le \tau_{max} \quad , \quad t\epsilon T \tag{6-34}$$

$$u_s^{S}, u_t^{T}, a_{st} \,\epsilon \{0,1\} \quad , \quad t\epsilon T, s\epsilon S \tag{6-35}$$

$$X_{iks}^{S}, X_{ikt}^{T}, Y_{ijt}^{T}, Y_{ijs}^{S}, O_{ikst}^{l} \epsilon \{0,1\} \quad , \quad i, j\epsilon N, k\epsilon K, l\epsilon O, t\epsilon T, s\epsilon S \tag{6-36}$$

$$q_{ks}^{S}, q_{kt}^{T}, Z_{iks}^{S}, Z_{ikt}^{T} \ge 0 \quad , \; i\epsilon N, k\epsilon K, t\epsilon T, s\epsilon S \tag{6-37}$$

The first objective function minimizes the total cost. The first two parts show the cost of using a truck and a trailer, respectively. The next two sections show the costs incurred by trucks and trailers, respectively. The last three sections show the costs of total travel time, service time, and total time spent on exchange operations, respectively.

The second objective function is to minimize environmental pollution.

Limitation 6-1 ensures that any trailer used must be assigned to the truck. Limit 6-2 ensures that each truck used can be connected to a maximum of one trailer.

Limitation 6-3 implies that at most k times at most one node must be visited if a truck is used.

Limitation 6-4 implies that at any k moment a maximum of one node must be visited if a trailer is used.

Limitation 6-5 indicates that if a truck (trailer) is used, it must start moving from the depot node.

Limitation 6-6 guarantees that if a truck (trailer) is used, it must be returned to the warehouse in an instant.

Limitations 6-7 and 6-8 show that if a truck (trailer) is used and meets the depot node at moment h and less than moment k, it cannot meet any other node at moment h.

Limitations 6-9 and 6-10 mean that a truck and a trailer cannot stay in a knot at the same time, respectively, and expect a trailer to be able to stay in exchange locations.

Limitation 6-11 ensures that each customer is met exactly once.

Limitation 6-12 ensures that a trailer cannot pass between two nodes unless it is attached to a truck.

Limitation 6-13 indicates that if a trailer is not attached to a truck, it does not allow the truck to meet the exchange location i at the k moment.

Limitation 6-14 guarantees that if the truck meets exchange location i at the moment k and the trailer is at exchange location, then operations P and U must be performed otherwise this restriction is additional and must be removed.

Limitation 6-15 ensures that if the truck meets exchange location i at the k moment with the corresponding trailer, then operations W and E must be performed, otherwise this constraint is additional and must be removed.

Limitations 6-16 to 6-18 mean that if the trailer is parked at the exchange point at moment K, it must remain at + k the next moment .Limitation 6-19 means that if the pickup operation is performed at a moment, a trailer must replace the place where it was parked. Restrictions 6-20 to 6-23 mean that if an exchange or replacement operation is performed, loads will be exchanged between the truck and the trailer. Limits 6-24 to 6-26 meet customer demand.

Limitations 6-27 and 6-28 ensure that the exchange load does not exceed capacity. Calculates the limits of 6-29 and 6-30 times exchanged after visiting the customer at the moment k. If the customer does not meet, swap or exchange operations are performed and these restrictions are considered redundant.

Limitation 6-31 ensures that if this is not allowed, the truck with a trailer attached to it will not visit the customer.

Limitation 6-32 indicates whether the truck is moving from i to j.

Limitation 6-33 indicates whether the trailer is moving from i to j.

Limitation 6-334 imposes a high limit on tour duration.

Limitation 6-35 to 6-37 also shows the range of problem variables.

The present study examines the truck and trailer routing problem, which is a generalization of VRP. The main differences between this research and VRP are: The vehicle fleet consists of a truck, a semi-trailer, and a swap body. A truck can have a swap body and a train (truck with a trailer) that has two swap bodies. There are restrictions on customer access, meaning that not all customers are allowed to be serviced by train. A set of trailer swap locations and swap bodies is provided. This problem was solved as a multi-objective problem of an integer programming model using GAMS software. Heuristic and meta-heuristic algorithms were used to solve the problem. The results of ten intervals are shown in Table 2:

Table 2: Values of the objective function of solving the example in GAMS

No.	Value of first objective function	Value of second objective function
1	22560	0
2	7010	477
3	35760	2279
4	22410	5426
5	22410	2279
6	24760	2279
7	24610	2279
8	22860	2279
9	22410	2279
10	27360	15956

The results are also shown schematically in the following figure:

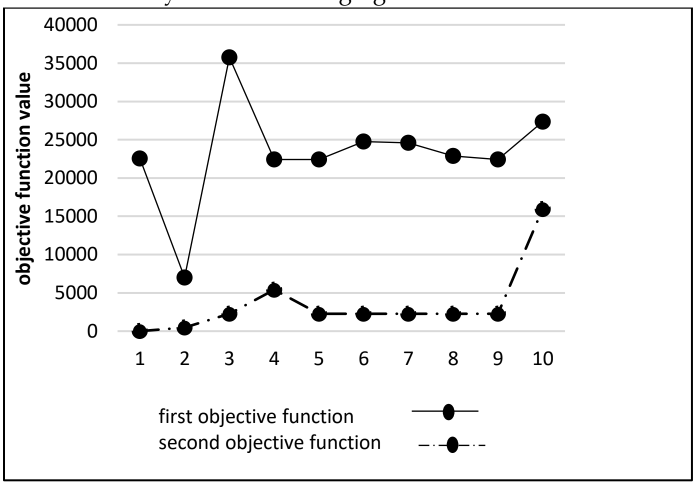

Figure 3: Values obtained from solving the GAMS example

4. Data analysis and discussion

In the preceding section, we defined the problem, constructed, and solved the mathematical model. Additionally, the model has been validated. This section will solve the mathematical model using two meta-heuristic algorithms, NSGA-II and MOPSO, and determine which of the two algorithms performs the best. To accomplish this, 100 problems were created in three categories: small, medium, and large, based on the number of train passengers, truck passengers, and exchange locations. Following a description of the dimensions of the generated problems, we will discuss the results obtained using the NSGA-II and MOPSO algorithms, followed by an analysis of the results. As an illustration, we've created a function in the MATLAB software that generates the desired example. The parameter ranges for the generated problems are listed in Table 3.

Table 3: Range of generated parameters

q_i	Rand (100,500)
S_i	Rand (10,20)
ρ_l	Rand (50,150)
t_{ij}	$d_{ij}/20$
d_{ij}	Rand (100,200)
C_F^T	Rand (1000,2000)
C_F^S	Rand (5000,10000)
C_D^T	Rand (1000,2000)
C_D^S	Rand (5000,10000)
C_T	Rand (100,200)
$Pull^t$	Rand (1,10)
$Pull^s$	Rand (1,10)

Table 4 details the dimensions of the generated problems. The first column in this table indicates the problem number. The second through fifth columns indicate the total number of customers, train customers, truck customers, and exchange locations, respectively. The Comparison of algorithms' performance contains the results of solving NSGA-II and MOPSO algorithms. The first column of these tables contains the problem number, while the second to fifth columns contain the criteria for solution time, Pareto answers, proximity to the ideal answer, maximum expansion, and spacing. Additionally, the final row of these tables contains the average of the available values. In this section, we will compare the results obtained using various methods for solving the NSGA-II and MOPSO algorithms. The various methods of comparison that Appendix 6 contains a comparison of the results using the solution time criterion.

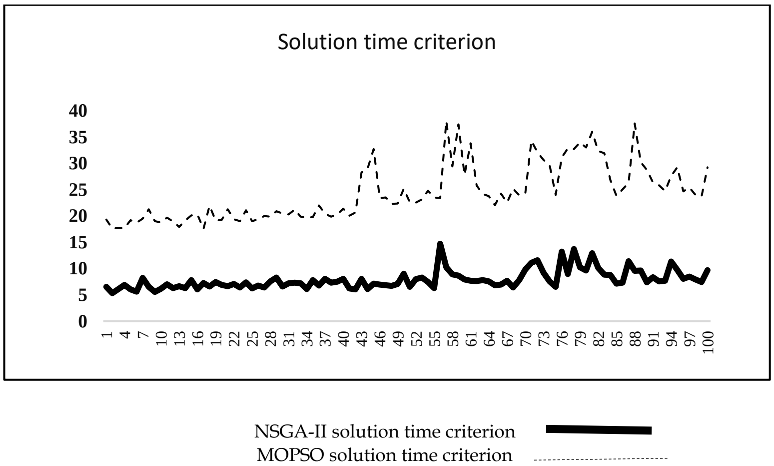

Figure 4: Comparison of the results based on the solution time criterion

The fluctuations between the two desired points in Figure 1 are almost parallel. Although these parallels share one criterion, they are separated by a time difference. In the MOPSO solution time criterion, the solution is solved with less time interval in 100 examples. It is quite clear that there is even a much larger time difference among examples 57 to 61. The comparison based on the solution time criterion shows that MOPSO algorithm has led to a solution in less time and therefore performed better in terms of time.
In this section, we examine which algorithm has performed better several times in each criterion. The results are given in Table 4.

Table 4: Comparison of algorithms based on the number of best solutions

	CPU Time	NPS	MID	Diversity	Spacing
NSGA-II	0	20	0	46	100
MOPSO	100	70	100	54	0

Comparison of algorithms' performance According to Solving time criterion, the MOPSO algorithm is not ok and NSGA-II is ok giving the best solution for all problems (100% of cases) in terms of solving time criteria.

In this section, we will compare the results based on statistical analysis using MINITAB 17 software. For this purpose, we should perform the normality test of the data. If the data are normally distributed, we would use the t-test to analyze the variance, otherwise, we would use the non-parametric Kruskal-Wallis test to analyze the variance. Moreover, it should be noted that we will examine the hypothesis of mean zero at 95 percent confidence level.

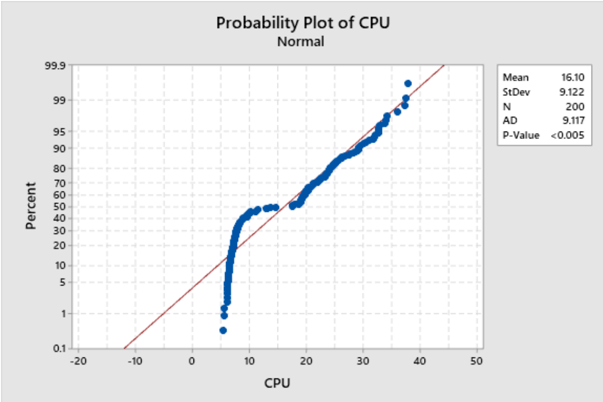

Figure 5: Comparison of the Results of Metaheuristic Algorithms for CPU Time

A comparison of the results of the meta-heuristic algorithms per run time (CPU Time) is shown in Figure 5. Based on the P-value of the test which was less than 0.05, it is concluded that the null hypothesis of normal distribution of data is rejected, and therefore the data is not normally distributed. Therefore, non-parametric Kruskal-Wallis test was used for statistical analysis.

Test

Null hypothesis H_0: All medians are equal

Alternative hypothesis H_1: At least one median is different

DF	H-Value	P-Value
100	174.13	0.000

Regarding the P-Value which is equal to zero, it is concluded that the null hypothesis indicating the equality of the mean of the two populations is rejected, and therefore there is a significant difference between the mean of the two populations.

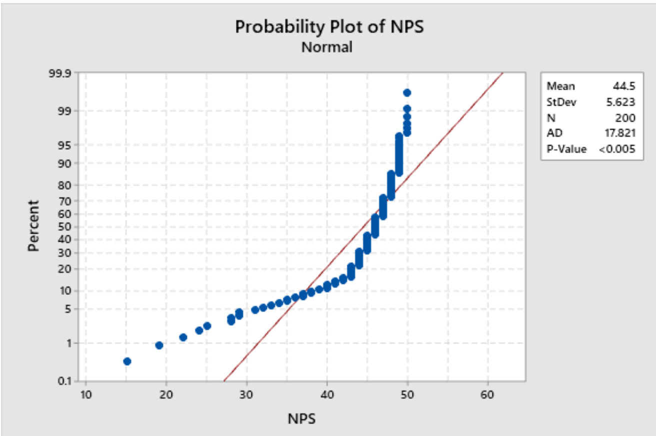

Figure 6: The result of the data normality test in the criterion of maximum NPS expansion

A comparison of the results of meta-heuristic algorithms for the NPS criterion is shown in Figure 6. Based on the P-value of the test which is less than 0.05, it is concluded that the null hypothesis indicating the normal distribution of data is rejected and therefore the data did not have a normal distribution. Therefore, nonparametric Kruskal-Wallis test will be used for statistical analysis. Based on the P-value of the test which is less than 0.05, it is concluded that the null hypothesis indicating the equality of the mean of two populations is rejected and therefore there is a significant difference in the mean of the two populations.

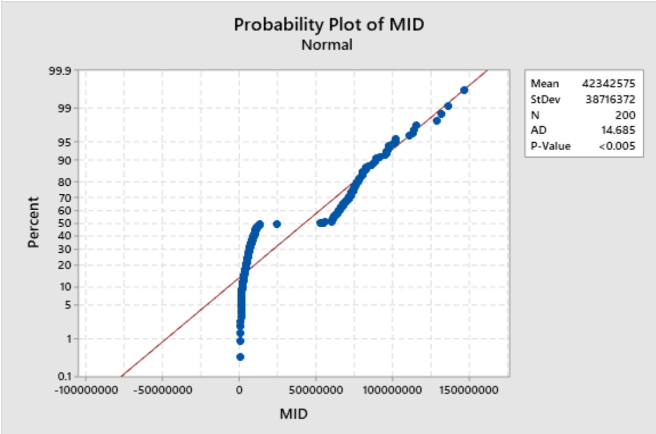

Figure 7: The result of the data normality test in the MID criterion

The results of comparing the results of meta-heuristic algorithms per MID criterion are shown in Figure 7. Based on the P-value of the test, which is less than 0.05, it is concluded that the null hypothesis of normal distribution of data is rejected and therefore the data did not have a normal distribution. Therefore, non-parametric Kruskal-Wallis test was used for statistical analysis. So, the null hypothesis of the equality of there is a significant difference in the mean of the two populations.

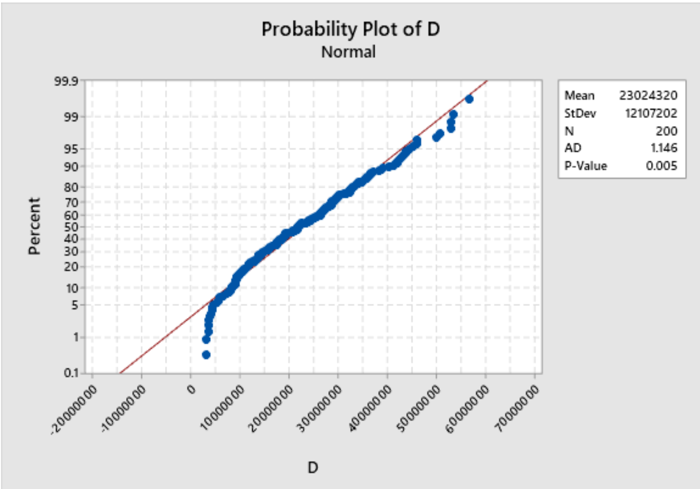

Figure 8: The result of the data normality test in the maximum expansion criterion

A comparison of the results of the meta-heuristic algorithms for the maximum expansion criterion is shown in Figure 5. Based on the P-value of the test, which is 0.005, it is concluded that the null hypothesis of normal data distribution is rejected and therefore the data did not have a normal distribution. Therefore, Kruskal-Wallis non-parametric test will be used for statistical analysis. So, it is concluded that the null hypothesis indicating the equality of the mean of two populations is rejected and therefore there is a significant difference in the mean of the two populations.

Table 5: Decision matrix for the proposed model

	CPU Time	NPS	MID	D
NSGA-II	24/31	42/54	78739740	22853600
MOPSO	7/78	46/46	5945410	23195040

The decision matrix presented in Table 5 shows the comparison of the results of meta-heuristic algorithms per execution time (CPU Time). The MOPSO method takes less time in giving a solution than the NSGA-II method. Therefore, the data normality test in the NPS criterion for the MOPSO metaheuristic algorithm shows a better number. Also, as a result of data normality test in the MID criterion, MOPSO is more efficient than the NSGA-II. The weighted criteria matrix is shown in Table 7. Here we assign the same weight to each of the criteria.

Table 6: Weights defined for each criterion

CPU Time	NPS	MID	D
0/2	0/2	0/2	0/2

In the next step, the unscaled matrix must be calculated. For this purpose, relation 7 is used. The result is shown in Table 7.

$$\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{7}$$

Table 7: Unscaled matrix

	CPU Time	NPS	MID	D
NSGA-II	0/9524	0/6753	0/9972	0/7018
MOPSO	0/3048	0/7375	0/0753	0/7123

In the next step, the weighted unscaled matrix must be calculated. The result is shown in Table 9.

Table 8: Weighted unscaled matrix

	CPU Time	NPS	MID	D
NSGA-II	0/1905	0/1351	0/1994	0/1404
MOPSO	0/0610	0/1475	0/0151	0/1425

In the next step, the positive and negative ideal points must be calculated. The result is shown in Table 9.

Table 9: positive and negative ideal points

	CPU Time	NPS	MID	D
NSGA-II	0/0610	0/1475	0/0151	0/1425
MOPSO	0/1905	0/1351	0/1994	0/1404

The next step is to get the distance of each option to the positive and negative ideals. For this purpose, we use relations 8 and 9. The results are shown in Table 10:

$$d_i^+ = \sqrt{\sum_{i=1}^{m} \left(v_{ij} - v_j^+\right)^2} \tag{8}$$

$$d_i^- = \sqrt{\sum_{i=1}^{m} \left(v_{ij} - v_j^-\right)^2} \tag{9}$$

Table 10: Calculating the relative proximity of an option to the ideal solution

Algorithms	the relative proximity of an option to the ideal solution	Rank
NSGA-II	0/1271	2
MOPSO	0/8729	1

According to the results of the similarity index and ranking of options, the closer this index is to the number one, shows the superiority of that option. Given that in the MOPSO algorithm, the desired number is 0.87, compared to the algorithm NSGA-II which is 0.12 and 0.87, is closer to one and as a result, MOPSO algorithm has better performance.

5. Conclusion

Nowadays, increasing speed, quality, and services to achieve competitive advantages in business have been considered by manufacturers and distributors as well as customers and stakeholders. The need for this issue in industrial and managerial fields has received more attention from scholars and academics. Moreover, with the increasing progress in transportation technology and dealing with energy loss and reducing casualties in accidents, and observing the economic savings of supply chain management in the field of transportation is of great importance and fortunately, this approach has developed substantially. Sustainable vehicle routing management is one of the pillars of sustainable futuristic supply chain management considering social and environmental utility. The present study proposed a multi-objective nonlinear model to develop the problem of sustainable vehicle (truck) routing. While including planning decisions to determine the ideal path and other existing conditions, the methodologies employed in this research consist of two main steps: The first step examines options concerning trains, trucks, and points of exchange; the second step examines judgments about best routes that minimize costs, time, and pollution. Regarding the Pareto solution time criterion, the MOPSO algorithm has the best performance by giving the best answer in 70 problems (70% of cases). In this criterion, NSGA-II algorithm is better in

20% of cases, and in 10%, the two algorithms have achieved the same result. Regarding the proximity to the ideal solution, MOPSO has the best performance by giving the best solution in all problems (100% of cases). Regarding the criterion of maximum expansion, MOPSO algorithm in 54 cases and NSGA-II algorithm in 46 cases have the best answer, respectively. Future research can include the development of other heuristic and meta-heuristic methods to solve the model, as well as modeling the problem, considering other goals such as maximizing customer satisfaction. Results show that the model designed in the present study can suggest optimal models for solving the sustainable vehicle (truck) routing problem considering the economic desirability using a multi-objective approach. These models have a significant impact on reducing costs and risks and environmental pollution.

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