

PROVIDING AN INTEGRATED MULTI-DEPOT VEHICLE ROUTING PROBLEM MODEL WITH SIMULTANEOUS PICKUP AND DELIVERY AND PACKAGE LAYOUT UNDER UNCERTAINTY WITH FUZZY-ROBUST BOX OPTIMIZATION METHOD

Mohammad Khodashenas¹, Seyed Esmaeel Najafi^{1*}, Hamed Kazemipoor² and Farzad Movahedi Sobhani¹

¹Department of Industrial Engineering, Islamic Azad University, Science and Research Branch, Tehran, Iran

²Department of Industrial Engineering, Islamic Azad University, Central Tehran Branch, Tehran, Iran

Received: 2 January 2023;

Accepted: 7 June 2023;

Available online: 4 July 2023.

Original scientific paper

Abstract: *This paper modeled and solved an integrated multi-depot vehicle routing problem (MDVRP) with simultaneous pickup and delivery (SPD) with package layout under unpredictable pickup, delivery, and transfer costs. The model described in this paper is divided into two stages. In the first stage, the SCA algorithm is used to optimize the package dimensions (a collection of commodities consumers need). The NSGA II and MOALO algorithms are used in the second stage to optimize the three objective functions of 1) simultaneously minimizing total costs, 2) minimizing CO₂ emissions, and 3) minimizing the maximum working hours of drivers based on the optimal dimensions (length, width, and height) obtained from solving the first stage model. Determining the quantity and ideal location of possible warehouses, the best route for trucks to take to deliver and collect customer items, and the distribution of customers to warehouses are the key goals of the second stage. Since the model is unclear, the problem's uncertainty parameters are controlled using a novel fuzzy-robust box optimization (FRBO) technique. This technique, which combines the advantages of fuzzy programming with robust box-based optimization, produces excellent results when used to optimize objective functions. The numerical calculations in the numerical example show that the total network costs and CO₂ emissions increased in the second stage in the presented model with an increasing uncertainty rate. At the same time, the maximum working hours of drivers decreased due to the shortened communication route and the number of vehicles*

* Corresponding author.

E- mail addresses: E.najafi@srbiau.ac.ir

Providing an integrated multi-depot vehicle routing problem model with simultaneous...
increasing. Finally, the MOALO algorithm was used to resolve a case study at Safir Broadcasting Company because of its excellent efficiency in resolving the created model, the findings of which revealed the presence of 13 potential effective solutions. The quantity of greenhouse gas emissions rose by 1.11%, the overall expenditures climbed by 1.72%, and the number of hours that drivers worked fell by 11.98% when the uncertainty rate was raised from 0.5 to 0.7, according to research on the FRBO.

Key words: MDVRP, SPD, package layout, MOALO, FRBO.

1. Introduction

The movement of people and commodities is an issue whose complexity is continually rising due to the increasing expansion of urbanization, industries, and support industries. This has made the problem more challenging to solve. The growth of cities has led to an increase in the demand placed on the transportation sector. This, in turn, has led to a rise in the number of challenges faced by cities and large industries, including but not limited to traffic congestion; air pollution; the inefficiency of long journeys; increased fuel consumption; vehicle depreciation; and so on. It is necessary to have a transportation system that is both well-equipped and efficient to alleviate traffic difficulties and the subsequent economic, social, and environmental issues that they cause in big cities, manufacturing enterprises, and service-oriented businesses. The transportation industry is not only one of the most significant contributors to the overall cost of completed goods but also one of the most significant contributors to the overall economy of any nation. According to (Koç et al., 2020), one of the difficulties explored in the literature on operations, distribution of commodities, movement of people, and transportation is the problem of vehicle routing. In 1959, Dantzig and Ramser were the ones who first brought up the problem of vehicle routing (Dantzig & Ramser, 1959). This is a combination of the two problems of the traveling salesman and the packing of boxes, which involves attempting to optimally design a set of routes for the transport fleet so that a certain number of customers are served while also having a limited number of ancillary capabilities. Because there is such a wide range of distinct iterations of this issue, it is very challenging and time consuming to categorize the many ways in which it manifests and to explain the various stages in which it does so. An extended model of the research conducted by Dantzig and Ramser (1959) is the problem of MDVRP with SPD. This problem combines two problems, including potential warehouse location and vehicle routing (Ma et al., 2019).

Because of the high costs involved, choosing possible warehouses is the most important strategic choice in a problem of this kind. Because of this, the aim in the first place is to pick potential warehouses as a strategic decision in the issue (Avcı & Topaloglu, 2016). The second choice that had to be taken concerning this matter concerned the routing of customers who have needs for various commodities and want to provide consumables (Kartal et al., 2017). In this scenario, each vehicle chooses a path for its traffic to be able to meet the demand of a group of customers based on constraints such as vehicle capacity, time window restrictions, and other such constraints, as well as to pick up customers' discarded goods and again deliver those goods to the customers (Belgin et al., 2018; Lagos et al., 2018). As a result, judgments about MDVRP and strategic SPD are made, as well as decisions regarding strategic and tactical aspects.

In such situations, the objective is to cut down as much as possible on the overall cost of where the warehouse is located and how the vehicles get there. The majority of research done on vehicle navigation issues has focused on finding ways to cut the costs associated with logistics. However, the quantity of goods distribution trucks has increased CO₂ emissions in the modern era. A lack of adequate planning has resulted in an imbalance in the time drivers spend working to transport and collect items from consumers. As a result, studies need to evaluate economic elements and pay greater attention to the model's capacity to maintain its stability.

In light of the significance of considering social and environmental factors, the challenge of devising a sustainable truck routing that allows for SPD is investigated in this work. The volume of SPD from clients is another crucial aspect of vehicle routing that must be determined. It is difficult or impossible to determine the exact amount of SPD for the construction of storage warehouses and the allocation of vehicles due to the uncertainty in the real-world environment, which can lead to increased logistics costs in some cases. This makes it challenging to plan for the construction of storage warehouses. As a result, there will be a shift in the total number of packages put in vehicles whenever there is a change in the volume of SPD. As a result, various vehicles have to be employed following the kind of client orders and the quantity of those orders. Each client has its unique preferences for how Bytes should, after the review, be organized into delivering bundles and placed in the appropriate vehicles. Because of this problem, a two-stage model has been developed in this article. In the first stage, the items in the various packages are placed in such a manner as to obtain the most ideal dimensions possible. This is done following the client's demands (length, width, and height).

After identifying the most efficient dimensions for each item concerning the capacity of the vehicles, the packages are reorganized inside the cars, and the most effective route for transportation is plotted out.

As a result, the model examined in this study may be represented as follows in two stages:

- The best product layout that can be SPD to customers in the first stage focuses on giving customers a priority.
- The best placement of potential warehouses and the best routing of vehicles for SPD in the second stage, focusing on minimizing the problem's overall cost, minimizing the CO₂ emissions, and minimizing the maximum driving hours.

Since there is uncertainty in the amount of SPD, the RFBO method is used. This method has the advantage of two fuzzy programming methods and a robust box optimization method in controlling uncertain parameters and optimizing the multiobjective model.

As a result, in this article, a two-stage model of MDVRP and SPD is modeled and assessed. This model also includes modeling of the layout and position of vehicles. The history of the relevant study and modeling of the issue will be described in the following parts. The following is an outline of the article's structure:

The second half of this analysis focuses on the literature review of the problem and the research gaps associated with the issue. In the third part of the article, there is a presentation of a two-stage model of MDVRP, which includes SPD. The fourth part discusses the problem's primary chromosome and the strategies employed to solve the problem. In the fifth section, we solve the issue by breaking it down into smaller pieces and looking at a case study with Safir Broadcasting Company. The last part is the conclusion, offering some ideas for further research.

2- Literature Review

Because the problem of vehicle routing is so essential, it has received a great deal of attention and research in recent decades, leading to various breakthroughs and solutions. One of the topics lately studied about the problem of routing is the issue of green vehicle routing. This kind of routing aims to route cars to minimize their impact on the environment and their need for fuel. Concerns about the routing of environmentally friendly vehicles may be grouped into three categories: routing with optimum fuel usage, routing that considers environmental pollutants, and routing that involves a reverse supply chain.

A model known as minimization of energy consumption in the problem of vehicle routing was presented on the topic of routing with fuel consumption optimization. This approach minimizes total energy use (Kara et al., 2007). The investigation's objective function was the product of the vehicle's weight, and the distance traveled. The issue of routing two-echelon vehicles with cross-docking in a supply chain network (suppliers, cross-warehouses, retailers). This was accomplished using the GA and the local search method (Ahmadizar et al., 2015). Kalayci and Kaya (2016) researched the ACO to identify the best solution to an issue with vehicle routing that included SPD. This research is being done to reduce the overall distance that freight trucks have to travel. Because better results presented in a shorter time in the benchmark data set are a good performance indicator, numerical results confirm that the developed method is powerful and very efficient regarding solution quality and CPU time. This is because better results are presented in the benchmark data set in a shorter time.

When preparing potentially hazardous materials and transporting products to and from various warehouses and ultimately to end users, a fuzzy linear programming model was developed to reduce the associated risk as much as possible. PSO, GA, SA, and ACO were the four meta-heuristic methods used to find a solution to the issue. Numerical examples were used to compare the various suggested techniques (Du et al., 2017). Brandão (2018) created an open VRP with a time window in mind, and to solve it, he used an iterative local search approach. This approach was used for data sets of larger sizes and applied to 418 example issues throughout its implementation. According to Brandão (2018), the findings demonstrated that this algorithm is quite effective at resolving problems of a grander scale.

In a publication by Polyakovskiy and M'Hallah (2018), the challenge of organizing goods in a two-dimensional space was investigated and modeled. To do this, they provided a complicated integer linear programming model and used CPLEX software to solve the model in various sizes. They also

Ulmer et al. (2021) posed the challenge of determining the most efficient truck routes to fulfill meal requests from many establishments simultaneously. This article's objective is to provide a method for dynamically controlling the drivers' fleet in such a manner as to circumvent delays in customer rules. Two different things may go wrong. First, the client's identity is not determined until the order has been placed. Second, there is no way to find out how long it takes for the restaurant to prepare the dish. An ACA is being considered as a potential solution to these problems (Ulmer et al., 2021). Curtois et al. (2018) developed a local search approach as a solution to the issue of vehicle routing, taking into account SPD and a time window. This article aims to use the distance minimization function to determine how many depots there should be and how vehicles should be routed between them. The suggested algorithm design has resulted in a technique that is both effective and quick, which locates many of the most well-known novel answers in a benchmark data set that is already well-known (Curtois et al.,

2018). Dambakk (2019) modeled a naval routing issue in his dissertation by considering simultaneous delivery and pickup, adding time windows and cost limitations, and so on. In light of the NP-Hard character of the challenge, he offered a time-saving algorithm to solve his model. The findings demonstrated that his suggested solution method effectively resolved the issue (Dambakk, 2019).

Another integer linear programming issue for a vehicle location-routing model with SPD was described by Hemmati Golsefidi and Akbari Jokar (2020). The model also considers the movement of goods in the opposite direction. The suggested model plans reproduction settings, reproduction amounts, retailer visits, supplier inventory management, retailer inventory management under vendor management, and retailer visits to reduce system costs. The problem of MDVRP with SPD was designed by Nadizadeh and Kafash (2019). They began with the premise that demand is unpredictable. They utilized the fuzzy programming method to control the demand parameter's unpredictability. The optimal values of two categories of model parameters, known as "vehicle indices" and "warehouse indices," were determined using numerical experiments, and the effects of these parameters on the overall solution were investigated. In a publication by Li et al. (2019), the primary objective was to identify the most efficient placement of warehouses and routes for delivery vehicles. They were able to resolve the issue by using the firewall algorithm. In a recent investigation, researchers Sadati et al. (2020) presented a skeleton game to determine the most cost-effective placement of warehouses and transportation routes to save expenses. At the first level, the decision maker acts as a leader to choose the best possible site for the facility. At the second level, the double decision maker serves as the leader in selecting the best possible route for the vehicles.

Zhang et al. (2019) considered an issue with multi-depot green vehicle routing (MDGVRP). As a solution to the problem, they suggested using an algorithm similar to that of an ACO. In this piece of research, a significant limitation, known as vehicle capacity, is included in the model to give it more significance and bring it closer to the actual world Dell'Amico et al. (2020) describe how the researchers solved their model by applying the precise branch and pricing method to their issue and analyzing it under a variety of conditions. Spencer et al. (2019) developed a scheme for organizing products into containers intended for cold things. The primary objective of these researchers in this article was to cut down on the number of packages utilized, lower the average beginning temperature of each shipment and reduce the time it took to deliver the product to the consumer. To solve their model, they used a greedy method. Wang and Lu (2021) found an optimal solution to the MDVRP by doing SPD. They created a model of the issue based on the clustering of consumer demand and the time frame limitations. They put their idea into action on a logistical network in China. Casazza et al. (2021) used a branch-and-price algorithm to handle the SPD issue that arose while trying to route vehicles. The findings indicate that the approach that they offered resulted in a decrease in the amount of time needed for computing. The MDVRP was established by Ky Phuc and Phuong Thao (2021), who then used the ACO to find a solution to the model. They took into account the capacity limits of the fleet as well as the time frame. do C. Martins et al. (2021) worked on modeling and addressing an MDVRP with simultaneous pickup and delivery to cut down on the expenses associated with logistics. They offered a novel way and demonstrated that the method that was suggested leads to a decrease in the amount of computational volume. Ghahremani-Nahr et al. (2022) designed a combined transportation model for the fruit and vegetable supply chain network. They used SCA and GA algorithms to solve the model.

Providing an integrated multi-depot vehicle routing problem model with simultaneous...

Table 1 investigates the research gap on two-stage MDVRP and SPD and the optimum placement of products in conveyors. This challenge requires modeling vehicle routing in two stages continuously.

According to the research that has been done on the topic and the analysis of the gaps in the study, it is possible to conclude that there is no all-encompassing model that addresses both the issues of optimal arrangement of goods and MDVRP that involves SPD. As a result, a two-stage modeling of MDVRP that includes SPD, as well as the arrangement of items, is going to be presented in this study. Given the suggested NP-Hard model, we will use the NSGA II, MOALO, and SCA to address the issue more comprehensively (Case study: Safir Broadcasting Company). In this research, the SCA obtains the proper arrangement of items inside the vehicle (first stage). The NSGA II and MOALO are used to find the best routing of vehicles that allows for SPD (second stage).

3- Problem Definition

This article discusses modeling and solving an integrated MDVRP with SPD and packet arrangement. Hence the primary purpose of the paper lies in strategic and tactical decisions. According to Figure 1, several customers have uncertain demands for different goods, and several vehicles have been used to meet their demands. Therefore, according to goals such as minimizing total costs, minimizing CO₂ emissions and balancing drivers' working hours, each warehouse covers customers and demand by one or more vehicles and satisfies them. Therefore, the first strategic decision made in the network includes the selection of potential warehouses for the distribution of goods. After assigning the customers to each warehouse according to the stated restrictions and goals, the vehicles choose the best route between the customers and distribute the goods. In another decision, due to the vehicles' dimensionality, transferring all the customers' goods is impossible. Therefore the optimal arrangement of packages in their vehicles is of great importance, which is addressed in the presented model. The model under consideration considers two different issues simultaneously. In the first stage, the main objective is the optimal arrangement of the first-category products in packages. In the second stage, the main goal is the arrangement of packages in vehicles and the optimal routing of vehicle transportation. In addition to discussing routing, the issue of locating distribution centers to send packages is also addressed at this stage.

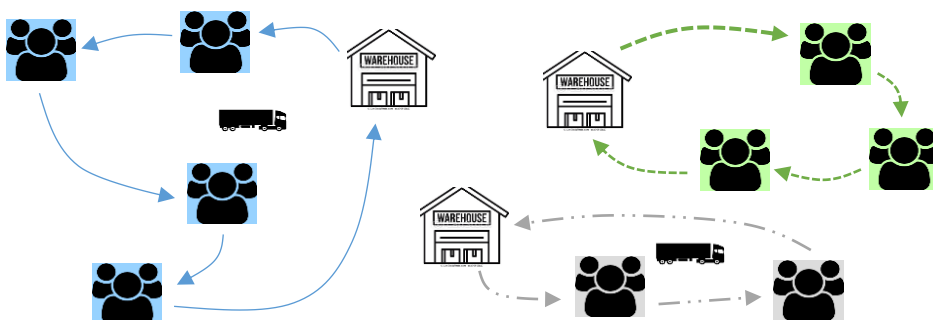


Figure 1. MDVRP and SPD

Table 1. Summary of research background in the field of vehicle routing and product layout

Author	Objective Function	Exact/ Uncertain	Warehouse	Solving Method	SPD	Product Layout	Social Responsibility	Case Study
Hadian et al. (2019)	1. min cost 2. min distance	exact	multi-warehouse	MOICA	-	-	-	-
Scheithauer (2018)	min number of packages	exact	-	hiuretic	-	*	-	-
Polyakovskiy and M'Hallah (2018)	min delay time	exact	-	Cplex	-	*	-	-
Curtois et al. (2018)	min distance	exact	-	local search	*	-	-	-
Spencer et al. (2019)	1. min number of packages 2- min delay time	exact	-	greedy algorithm	-	*	*	-
Zhang et al. (2019)	min transfer time	exact	multi-warehouse	ACA - SA	-	-	-	-
Ulmer et al. (2021)	min distance	uncertain	-	ACA	*	-	-	restaurants
Sadati et al. (2020)	min cost	exact	multi-warehouse	silkworm algorithm	-	-	-	-
Nadizadeh & Kafash (2019)	min cost	uncertain	multi-warehouse	CPLEX	*	-	*	-
Dell'Amico et al. (2020)	min number of packages	exact	-	branches and prices	-	*	-	-
Fu & Banerjee (2020)	min number of packages	exact	-	GA - SA	-	*	-	-
Wang & Lu (2021)	min cost	exact	multi-warehouse	hybrid algorithm	*	-	-	logistic
Casazza et al. (2021)	min cost	exact	multi-warehouse	branches and prices	*	-	-	-
Ky Phuc & Phuong Thao (2021)	min cost	exact	multi-warehouse	ant colony	*	-	-	-
do C. Martins et al. (2021)	min cost	exact	multi-warehouse	hiuretic	*	-	-	-
Current research	MDVRP and SPD	uncertain	multi-warehouse	NSGA II MOLAO - SCA	*	*	*	safir broadcasting company

Providing An Integrated Multi-Depot Vehicle Routing Problem Model With Simultaneous...

The primary purpose of the first modeling stage, as stated in the issue statement, is to reduce the dimensions (length, breadth, and height) of packages whose contents are goods with uncertain client demand. The primary goals of the second modeling stage are to focus on three sustainable aspects of the issue: social, economic, and environmental. The financial objective is to reduce the costs of locating distribution centers and transporting goods by vehicle (minimizing the maximum total working hours performed by each vehicle). Customer demand is one of the problem's uncertain characteristics; hence a novel technique for controlling uncertainty termed FRBO has been used. In this approach, the problem parameters are first considered fuzzy triangular numbers (optical and championship, 2019). The fuzzy model is then controlled using the robust-box optimization approach to regulate the uncertainty rate parameter (Zahedi & Nahr, 2020). The following suppositions may be used to describe the integrated MDVRP with SPD and package layout:

- The problem is considered multi-products,
- The sizes of the trucks used for the transportation of products are previously established and defined;
- The bundles of items to be transferred are known in advance for their size,
- Although the number of warehouses and their locations are unclear,
- Uncertain parameters of the problem are considered fuzzy triangular numbers.
- Uncertain demand parameter control is the FRBO method,
- The center of coordinates for the arrangement of packages in vehicles as well as products in packages is point (0,0),
- Uncertain customer demand for any product must be met,
- All second-hand products of customers must be picked up by the same vehicle after delivery of first-class products.

In the following, the parameters used in modeling are presented, and the final model is described:

Sets

$l \in L$	Distribution centers (warehouses)
$m, c \in C$	Customers
$p, p' \in P$	Products
$v \in V$	Vehicle
$n, n' \in N$	Nodes (distribution centers and customers)

Parameters

W_{cp}	The width of product p for customer c
L_{cp}	The length of product p for customer c
H_{cp}	The height of product p for customer c
U_l	Cost of establishing distribution center l
F_v	The fixed cost of using vehicle v
\tilde{D}_{cp}	The demand for product p to customer c ($\tilde{D}_{cp} = D_{cp}^1, D_{cp}^2, D_{cp}^3$)
\tilde{R}_{cp}	Return of product p from customer c ($\tilde{R}_{cp} = R_{cp}^1, R_{cp}^2, R_{cp}^3$)
$CapV_v$	The capacity of vehicle v
$CapL_{lp}$	The capacity of product p in the distribution center l
$Dis_{nn'}$	The far between node n and n'
$\tilde{T}r_{nn'}$	Non-deterministic transportation cost between node n and n' ($\tilde{T}r_{nn'} = Tr_{nn'}^1, Tr_{nn'}^2, Tr_{nn'}^3$)
$T_{nn'}$	Transport time between node n and n'

S_c	Time to unload and load the vehicle at node c
C_{lp}	Distribution cost of product p in distribution center l
$[AS_c, BS_c]$	The flexible time window for delivery and pickup of customer products c
α	Penalty cost for exceeding the soft time window
H	The amount of CO_2 gas emissions depends on the product
$Wmax_c$	The optimal package width determined for the customer c
$Lmax_c$	The optimal package length determined for the customer c
$Hmax_c$	The optimal package height determined for the customer c
WK_v	The width of vehicle v
LK_v	The length of vehicle v
Hk_v	The height of vehicle v
ρ	Uncertainty rate
M	Non-negative large number

Decision Variables

$Wmax_c$	Optimum package width for the customer c
$Lmax_c$	The optimal length of the package for customer c
$Hmax_c$	The optimal height of the package for customer c
X_{cp}	The length starting point of the product p arrangement for the package of customer c
Y_{cp}	The width starting point of the product p arrangement for the package of customer c
Z_{cp}	The height starting point of the product p arrangement for the package of customer c
$a_{cpp'}$	$\begin{cases} 1, & \text{If product } p \text{ is placed in front of product } p' \text{ for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
$b_{cpp'}$	$\begin{cases} 1, & \text{If product } p \text{ is placed to the right of product } p' \text{ for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
$c_{cpp'}$	$\begin{cases} 1, & \text{If product } p \text{ is placed above product } p' \text{ for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
Xl_{cp}	$\begin{cases} 1, & \text{If the length of the product } p \text{ is parallel to the X axis for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
Zl_{cp}	$\begin{cases} 1, & \text{If the length of the product } p \text{ is parallel to the Z axis for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
Yw_{cp}	$\begin{cases} 1, & \text{If the product width } p \text{ is parallel to the Y axis for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
$Zh_{r,i}$	$\begin{cases} 1, & \text{If the product height } p \text{ is parallel to the Z axis for the package of customer } c \\ 0, & \text{otherwise} \end{cases}$
V_{lpv}	Product p distributed from distribution center l by vehicle v
Z_l	$\begin{cases} 1, & \text{If the distribution center } l \text{ is established} \\ 0, & \text{otherwise} \end{cases}$
Z_{lcv}	$\begin{cases} 1, & \text{If distribution center } l \text{ is assigned to customer } c \text{ and vehicle } v \\ 0, & \text{otherwise} \end{cases}$
$X_{nn'v}$	$\begin{cases} 1, & \text{If node } n' \text{ is visited by vehicle } v \text{ after node } n \\ 0, & \text{otherwise} \end{cases}$
U_{cv}	Auxiliary variable
Tc_{lcv}	The time of vehicle v arriving at customer c and leaving the distribution center l
Tw_{lv}	The total time of the vehicle in picking up and delivering the goods to the assigned customers out of the distribution center l

Providing An Integrated Multi-Depot Vehicle Routing Problem Model With Simultaneous...

Lc_{cpv}	The amount of pickup product p by vehicle v at the customer node c
Te_{cv}	Exceeding the time window of vehicle v at customer c
Y'_{cpv}	$\begin{cases} 1, & \text{If the product } p \text{ of customer } c \text{ is transported by vehicle } v \\ 0, & \text{otherwise} \end{cases}$
Al_{cv}	$\begin{cases} 1, & \text{If the package of customer } c \text{ is assigned to vehicle } v \\ 0, & \text{otherwise} \end{cases}$
$Xl1_c$	$\begin{cases} 1, & \text{If the length of the customer package } c \text{ is parallel to the X axis} \\ 0, & \text{otherwise} \end{cases}$
$Yl1_c$	$\begin{cases} 1, & \text{If the length of the customer package } c \text{ is parallel to the Y axis} \\ 0, & \text{otherwise} \end{cases}$
$Xw1_c$	$\begin{cases} 1, & \text{If the width of the customer package } c \text{ is parallel to the X axis} \\ 0, & \text{otherwise} \end{cases}$
$Yw1_c$	$\begin{cases} 1, & \text{If the width of the customer package } c \text{ is parallel to the Y axis} \\ 0, & \text{otherwise} \end{cases}$
O_v	$\begin{cases} 1, & \text{If vehicle } v \text{ is used} \\ 0, & \text{otherwise} \end{cases}$
$X1_c$	The length starting point of the arrangement of the package of customer c in the vehicle
$Y1_c$	The width starting point of the arrangement of the package of customer c in the vehicle
$Z1_c$	The height starting point of the arrangement of the package of customer c in the vehicle
a'_{cm}	$\begin{cases} 1, & \text{If package } c \text{ is placed on the left side of package } m \\ 0, & \text{otherwise} \end{cases}$
b'_{cm}	$\begin{cases} 1, & \text{If package } c \text{ is placed on the right side of package } m \\ 0, & \text{otherwise} \end{cases}$
c'_{cm}	$\begin{cases} 1, & \text{If package } c \text{ is placed behind package } m \\ 0, & \text{otherwise} \end{cases}$
d'_{cm}	$\begin{cases} 1, & \text{If package } c \text{ is placed in front of package } m \\ 0, & \text{otherwise} \end{cases}$
e'_{cm}	$\begin{cases} 1, & \text{If package } c \text{ is placed under package } m \\ 0, & \text{otherwise} \end{cases}$
f'_{cm}	$\begin{cases} 1, & \text{If package } c \text{ is placed above package } m \\ 0, & \text{otherwise} \end{cases}$

Mathematical Model of The First Stage

$$\text{Min}Z = \sum_{c=1}^c (Wmax_c + Hmax_c + Lmax_c) \quad (1)$$

s. t.:

$$\begin{aligned} & X_{cp} + L_{cp} \cdot Xl_{cp} + W_{cp}(Zl_{cp} - Yw_{cp} + Zh_{cp}) \\ & + H_{cp}(1 - Xl_{cp} - Zl_{cp} + Yw_{cp} - Zh_{cp}) \\ & \leq X_{cp'} + M \cdot (1 - a_{cpp'}), \quad \forall c, p \neq p' \end{aligned} \quad (2)$$

$$\begin{aligned} & Y_{cp} + W_{cp} \cdot Yw_{cp} + L_{cp}(1 - Xl_{cp} - Zl_{cp}) + H_{cp}(Xl_{cp} + Zl_{cp} - Yw_{cp}) \\ & \leq Y_{cp'} + M \cdot (1 - b_{cpp'}), \quad \forall c, p \neq p' \end{aligned} \quad (3)$$

$$Z_{cp} + H_{cp} \cdot Zh_{cp} + W_{cp}(1 - Zl_{cp} - Zh_{cp}) + L_{cp}Zl_{cp} \leq Z_{cp}' + M \cdot (1 - c_{cpp}'), \quad \forall c, p \neq p' \tag{4}$$

$$X_{cp} + L_{cp} \cdot Xl_{cp} + W_{cp}(Zl_{cp} - Yw_{cp} + Zh_{cp}) + H_{cp}(1 - Xl_{cp} - Zl_{cp} + Yw_{cp} - Zh_{cp}) \leq Lmax_c, \quad \forall c, p \tag{5}$$

$$Y_{cp} + W_{cp} \cdot Yw_{cp} + L_{cp}(1 - Xl_{cp} - Zl_{cp}) + H_{cp}(Xl_{cp} + Zl_{cp} - Yw_{cp}) \leq Wmax_c, \quad \forall c, p \tag{6}$$

$$Z_{cp} + H_{cp} \cdot Zh_{cp} + W_{cp}(1 - Zl_{cp} - Zh_{cp}) + L_{cp} \cdot Zl_{cp} \leq Hmax_c, \quad \forall c, p \tag{7}$$

$$a_{cpp'} + a_{cp'p} + b_{cpp'} + b_{cp'p} + c_{cpp'} + c_{cp'p} \geq 1, \quad \forall c, p \neq p' \tag{8}$$

$$Xl_{cp} + Zl_{cp} \leq 1, \quad \forall c, p \tag{9}$$

$$Zl_{cp} + Zh_{cp} \leq 1, \quad \forall c, p \tag{10}$$

$$Zl_{cp} - Yw_{cp} + Zh_{cp} \leq 1, \quad \forall c, p \tag{11}$$

$$Zl_{cp} - Yw_{cp} + Zh_{cp} \geq 0, \quad \forall c, p \tag{12}$$

$$1 - Xl_{cp} - Zl_{cp} + Yw_{cp} - Zh_{cp} \leq 1, \quad \forall c, p \tag{13}$$

$$1 - Xl_{cp} - Zl_{cp} + Yw_{cp} - Zh_{cp} \geq 0, \quad \forall c, p \tag{14}$$

$$Xl_{cp} + Zl_{cp} - Yw_{cp} \leq 1, \quad \forall c, p \tag{15}$$

$$Xl_{cp} + Zl_{cp} - Yw_{cp} \geq 0, \quad \forall c, p \tag{16}$$

$$Wmax_c, Lmax_c, Hmax_c, X_{cp}, Y_{cp}, Z_{cp} \geq 0, \quad \forall c, p \tag{17}$$

$$a_{cpp'}, b_{cpp'}, c_{cpp'}, Xl_{cp}, Zl_{cp}, Yw_{cp}, Zh_{cp} \in \{0,1\}, \quad \forall c, p, p' \tag{18}$$

The Second Stage, Mathematical Model

$$Min\omega 1 \tag{19}$$

$$Min\omega 2 = \sum_{n=1}^N \sum_{n'=1}^N \sum_{v=1}^V \sum_{p=1}^P H \cdot Dis_{nn'} Lc_{nn'pv} \tag{20}$$

$$Min\omega 3 = max_x \{Tw_{lv}, \quad \forall l \in L, v \in V\} \tag{21}$$

s. t.:

$$\sum_{n=1}^N \sum_{n'=1}^N \sum_{v=1}^V \left(\left(\frac{Tr_{nn'}^1 + 2.Tr_{nn'}^2 + Tr_{nn'}^3}{4} \right) X_{nn'v} + \eta_{nn'v} \right) + \sum_{l=1}^L \sum_{p=1}^P \sum_{v=1}^V C_{lp} V_{lpv} \quad (22)$$

$$+ + \sum_{c=1}^C \sum_{v=1}^V \alpha T e_{cv} \leq \omega 1 - \sum_{v=1}^V F_v O_v - \sum_{l=1}^L U_l Z_l$$

$$\rho \left(\frac{Tr_{nn'}^1 + 2.Tr_{nn'}^2 + Tr_{nn'}^3}{4} \right) X_{nn'v} \leq \eta_{nn'v}, \quad \forall n, n', v \quad (23)$$

$$\rho \left(\frac{Tr_{nn'}^1 + 2.Tr_{nn'}^2 + Tr_{nn'}^3}{4} \right) X_{nn'v} \geq -\eta_{nn'v}, \quad \forall n, n', v \quad (24)$$

$$\sum_{v=1}^V \sum_{n=1}^N X_{lcv} = 1, \quad \forall c \quad (25)$$

$$\sum_{c=1}^C \sum_{n=1}^N \sum_{p=1}^P \left[(1 - \rho) \left(\frac{D_{cp}^1 + D_{cp}^2}{2} \right) + \rho \left(\frac{D_{cp}^2 + D_{cp}^3}{2} \right) \right] X_{ncv} \leq Cap V_v O_v, \quad \forall v \quad (26)$$

$$U_{cv} - U_{mv} + C.X_{cmv} \leq C - 1, \quad \forall m, c, v \quad (27)$$

$$\sum_{n=1}^N X_{ncv} = \sum_{n=1}^N X_{cnv}, \quad \forall v, n \quad (28)$$

$$\sum_{l=1}^L \sum_{c=1}^C X_{lcv} \leq 1, \quad \forall v \quad (29)$$

$$-Z_{lcv} + \sum_{n=1}^N (X_{lnv} + X_{ncv}) \leq 1, \quad \forall l, c, v \quad (30)$$

$$V_{lpv} = \sum_{c=1}^C \left[(1 - \rho) \left(\frac{D_{cp}^1 + D_{cp}^2}{2} \right) + \rho \left(\frac{D_{cp}^2 + D_{cp}^3}{2} \right) \right] Z_{lcv}, \quad \forall l, p, v \quad (31)$$

$$\sum_{v=1}^V V_{lpv} \leq Cap L_{lp} Z_l, \quad \forall l, p \quad (32)$$

$$L C_{lcpv} \geq V_{lpv} - \left[(1 - \rho) \left(\frac{D_{cp}^1 + D_{cp}^2}{2} \right) + \rho \left(\frac{D_{cp}^2 + D_{cp}^3}{2} \right) \right] \\ + \left[(1 - \rho) \left(\frac{R_{cp}^1 + R_{cp}^2}{2} \right) + \rho \left(\frac{R_{cp}^2 + R_{cp}^3}{2} \right) \right] \\ - M.(1 - X_{lcv}), \quad \forall l, p, c, v \quad (33)$$

$$Lc_{lmpv} \geq Lc_{lcpv} - \left[(1 - \rho) \left(\frac{D_{mp}^1 + D_{mp}^2}{2} \right) + \rho \left(\frac{D_{mp}^2 + D_{mp}^3}{2} \right) \right] + \left[(1 - \rho) \left(\frac{R_{mp}^1 + R_{mp}^2}{2} \right) + \rho \left(\frac{R_{mp}^2 + R_{mp}^3}{2} \right) \right] - M \cdot (1 - X_{cmv}), \quad \forall l, p, c, m, v \tag{34}$$

$$Tc_{lcv} \geq T_{lc} - M \cdot (1 - X_{lcv}), \quad \forall l, c, v \tag{35}$$

$$Tc_{lmv} \geq Tc_{lcv} + T_{cm} + S_m - M \cdot (2 - X_{cmv} - Z_{lcv}), \quad \forall l, c, m, v \tag{36}$$

$$Te_{cv} \geq AS_c \cdot Z_{lcv} - Tc_{lcv}, \quad \forall l, c, v \tag{37}$$

$$Te_{cv} \geq Tc_{lcv} - BS_c \cdot Z_{lcv}, \quad \forall l, c, v \tag{38}$$

$$Tw_{lv} \geq Tc_{lcv} + T_{cl} \cdot X_{clv}, \quad \forall l, c, v \tag{39}$$

$$\sum_{l=1}^L Lc_{lcpv} = Y'_{cpv}, \quad \forall c, p, v \tag{40}$$

$$\sum_{p=1}^P Y'_{cpv} \leq M * Al_{cv}, \quad \forall c, v \tag{41}$$

$$X1_c + Lmax_c Xl1_c + Wmax_c (1 - Xl1_c) \leq X1_m + M \cdot (1 - a'_{cm}), \quad \forall c < m \tag{42}$$

$$X1_m + Lmax_m Xl1_m + Wmax_m (1 - Xl1_m) \leq X1_c + M \cdot (1 - b'_{cm}), \quad \forall c < m \tag{43}$$

$$Y1_c + Wmax_c Xl1_c + Lmax_c (1 - Xl1_c) \leq Y1_m + M \cdot (1 - c'_{cm}), \quad \forall c < m \tag{44}$$

$$Y1_m + Wmax_m Xl1_m + Lmax_m (1 - Xl1_m) \leq Y1_c + M \cdot (1 - d'_{cm}), \quad \forall c < m \tag{45}$$

$$Z1_c + Hmax_c \leq Z1_m + M \cdot (1 - e'_{cm}), \quad \forall c < m \tag{46}$$

$$Z1_m + Hmax_m \leq Z1_c + M \cdot (1 - f'_{cm}), \quad \forall c < m \tag{47}$$

$$a'_{cm} + b'_{cm} + c'_{cm} + d'_{cm} + e'_{cm} + f'_{cm} \geq Al_{cv} + Al_{mc} - 1, \quad \forall v, c < m \tag{48}$$

$$\sum_{v=1}^V Al_{cv} = 1, \quad \forall c \tag{49}$$

$$X1_c + Lmax_c \cdot Xl1_c + Wmax_c \cdot Xw1_c \leq Lk_v + M \cdot (1 - Al_{cv}), \quad \forall c, v \tag{50}$$

$$Y1_c + Wmax_c \cdot Yw1_c + Lmax_c \cdot Yl1_c \leq WK_v + M \cdot (1 - Al_{cv}), \quad \forall c, v \tag{51}$$

$$Z1_c + Hmax_c \leq HK_v + M.(1 - Al_{cv}), \quad \forall c, v \quad (52)$$

$$\sum_{c=1}^c Al_{cv} \leq M.O_v, \quad \forall v \quad (53)$$

$$Yl1_c = 1 - Xl1_c, \quad \forall c \quad (54)$$

$$Xw1_c = 1 - Xl1_c, \quad \forall c \quad (55)$$

$$Yw1_c = Xl1_r, \quad \forall c \quad (56)$$

$$V_{l_{pv}}, U_{cv}, Tc_{lcv}, Tw_{lv}, Lc_{lcpv}, Te_{cv}, X1_c, Y1_c, Z1_c \geq 0 \quad (57)$$

$$Z_l, Z_{lcv}, X_{nn'v}, Al_{cv}, Yl1_c, Xl1_c, Xw1_c, Yw1_c, O_v, Y'_{cpv}, a'_{cm}, b'_{cm}, c'_{cm}, d'_{cm}, e'_{cm}, \in \{0,1\} \quad (58)$$

The objective function of the issue in the first phase is shown by Eq. (1). This function comprises reducing the package dimensions that have been developed for the layout of each customer's items as much as possible—the solution to Eqs. (2), (3), and (4) guarantees that the two products do not overlap with one another and do not overlap with one another. The constraints numbered five through seven ensure that the dimensions of the products remain unchanged; the only change that occurs is in the products' orientation concerning one another. The value of each product's location is indicated by the eighth constraint relating to the other nearby items. The constraints (9) to (16) ensure that each product's positioning inside the packaging is maintained following the planned dimensions. The choice variables' type and gender are denoted by the constraints (17) and (18), respectively.

The output of the aforementioned model in the first stage consists of first-hand goods of consumers packaged in containers with dimensions that are ideal for arrangement inside the vehicle. The model's second step covers determining the number of distribution centers, vehicle problem routing, and the organization of packets inside vehicles. This is done to achieve optimum package dimensions. The issue's first objective is to minimize the overall expenses of developing the supply chain vehicle routing network (19). This function seeks the optimal solution. These expenditures include the distribution center's building, transportation, and distribution. These costs include starting and running the vehicle and penalties for exceeding the time limit. Eq. (20) illustrates the second objective function of the issue, which entails reducing the total quantity of greenhouse gas emissions caused by the vehicle's load to the lowest possible value. The third objective function of the problem is represented by Eq. (21), and it includes the optimization of the standard time of vehicle traffic in the delivery and collection of the same products. Additionally, it minimizes the maximum traffic time of vehicles leaving each distribution center. Through the use of a solid box approach, the Eqs. (22) through (25) regulate the unknown parameters of the shipping cost. Eq. (26) ensures that each distribution center can only be assigned to one customer. Eq. (27) demonstrates the maximum amount of product that can be transported by a vehicle at any given time. Restriction (28) the limitation was put in place since the net that was underneath was removed. The vehicle can only enter and depart each client node once, as Constraint (29) stipulated, which guarantees this. Eq. (30) assures that only one vehicle can be allocated to each route generated by limiting the number of possible

vehicles. Eq. (31) illustrates the process of assigning each customer to a particular distribution center and also indicates that the vehicle must return to the distribution center after the process of visiting the client nodes has been completed. The answer to this question may be found in Eq. (32), which displays the total quantity of distribution carried out by each distribution center and vehicle. The solution to Eq. (33) ensures that the distribution center capacity will not be used until the center has been built. The quantity of load carried by each truck when it departs each distribution center for the first client visit is represented by Eq. (34). The Eq. (35) will tell you how much cargo is in each truck (the total number of deliveries and pickups) while you are traveling to different client nodes and then heading back to the distribution center. The time the truck arrived at the first client node after leaving the distribution center is represented by equation (36), which may be found below. The truck's arrival time at each client node is calculated using Eq. (37), which considers the time spent loading and unloading and the amount of time spent in traffic between the nodes. The length of time that the Eqs represent the vehicle overstays at each client node in the soft timeline. (38) and (39), which may be found below. Using Eq. (40), one may determine how long the truck will take to return to the distribution center after delivering and picking up the products.

The distribution of each package to each vehicle is computed using Eqs. (41) and (42), respectively. Eqs. (43) to (48) make sure that none of the packets overlap and that they cannot be stuffed inside one another. Eq. (49) guarantees that each packet may only be adjacent to the other individual packet in one of the six possible orientations. Eq. (50) demonstrates that each parcel can only be transported in a single automobile. The solutions to Eqs. (51) to (53) demonstrate that the packages' length, width, and height cannot exceed the vehicle's dimensions. The kind of loaded vehicle may be determined using Eq. (54). If Eqs. (55), (56), and (57) are followed, then the size of the packages will remain the same throughout loading, and the only thing that will vary is the kind of placement. Relationships (58) and (59) demonstrate the different types of choice factors broken down by gender.

Taking into account the one objective function of the mathematical model presented in the first stage as well as the three objective functions of the mathematical model shown in the second stage, the SCA Mirjalili (2016) was used to achieve a value of the objective function that was close to optimal in the first stage. The NSGA II and MOALO (Mirjalili, 2015) were utilized to achieve the Pareto front by solving the second-stage model. The parameters of the meta-heuristic algorithms used to solve the issue will be set in the following.

4. Solving Methods

This section sets the parameters and the chromosome design of the two-stage model presented in this paper. The problem optimization in the first stage with SCA and Pareto front formation in the second stage with MOALO and NSGA II are discussed.

4.1. Parameterization of Meta-Heuristic Algorithms

Parameters tuning of meta-heuristic approach to increase their efficiency in problem-solving in a shorter time and with greater accuracy. Therefore, each algorithm has its initial parameters that Bytes put in their best combination to solve the problem. Thus, Table 2 shows the basic parameters of each SCA, NSGA II, and MOALO. SCA determines the dimensions of packages to be sent to customers, and NSGA II and MOLAO are used to optimize the three-objective model in the second stage.

Table 2. Initial parameters tuning by the Taguchi method

Solution Method	Factor	L1	L2	L3
SCA	max it	100	150	200
	N pop	100	150	200
	a	1	2	3
NSGA II	max it	100	150	200
	N pop	100	150	200
	Pc	0.2	0.5	0.7
	Pm	0.2	0.5	0.7
MOALO	max it	100	150	200
	Npop	100	150	200
	A	1	2	3
	C	1	2	3

After determining the initial levels of each parameter, parameter tuning is done by the Taguchi method and based on predetermined tests. After performing each test with different combinations of the levels stated in Table 2, the mean of means and the mean of the S/N ratio has been obtained as described in Figures 2 to 4. The basis for choosing the optimal parameter levels and their value is the maximum level of each factor in the average S/N ratio diagram.

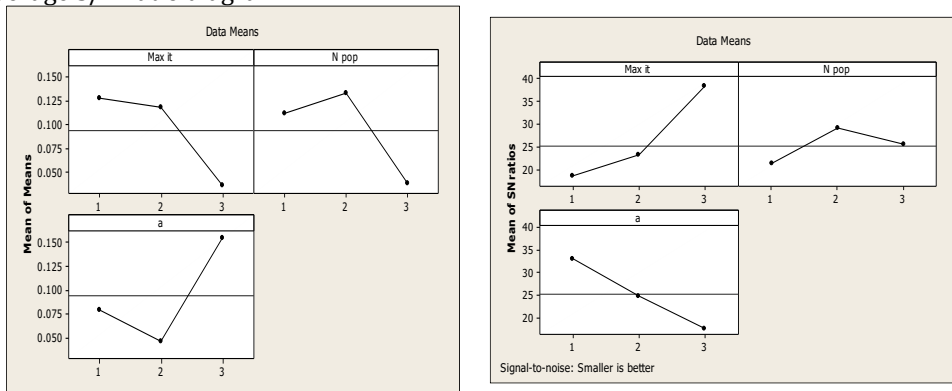


Figure 2. The mean of means and mean of S/N ratio for SCA

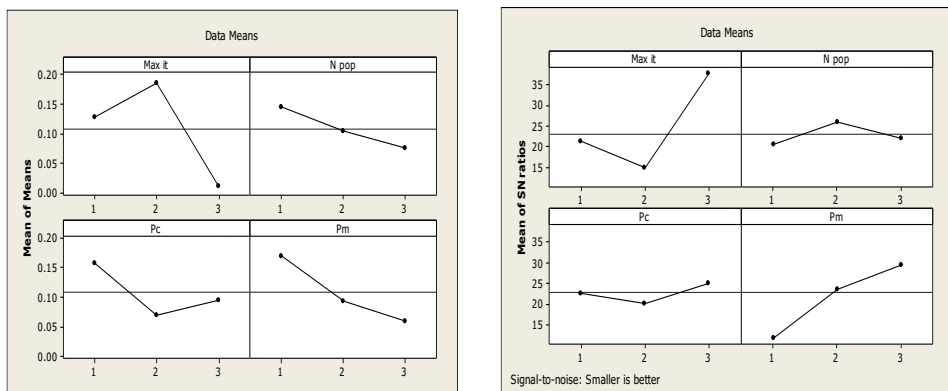


Figure 3. The mean of means and mean of S/N ratio for NSGA II

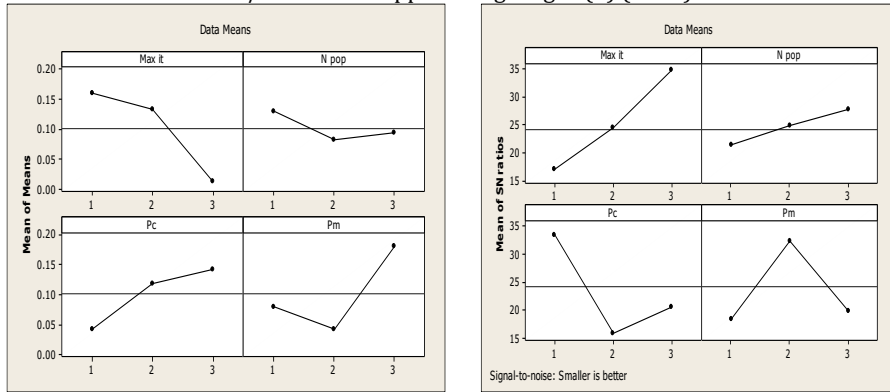


Figure 4. The mean of means and mean of S/N ratio for MOALO

The parameters' best level and value to increase their effectiveness in finding the optimum solution or the Pareto front are given in Table 3 format according to Figures 2 to 4.

Table 3. Levels and value of optimal parameters of meta-heuristic algorithms

Algorithm	Parameter	Level	Value
SCA	max it	L3	200
	N pop	L2	150
	a	L1	1
NSGA II	max it	L3	200
	N pop	L2	150
	Pc	L3	0.7
	Pm	L3	0.7
MOALO	max it	L3	200
	Npop	L3	200
	A	L1	1
	C	L2	2

4.2. Initial Solution of The Problem

The problem being studied in this article has two phases. The SCA method is used to optimize the packet dimensions. The first stage is to optimize the dimensions of each package for the customer. Consider a hypothetical scenario with two clients and three items to demonstrate how the chromosome is decoded. The sizes of each item the buyer wanted are shown in Table 4.


Table 4. Dimensions of products

Customer	Product		
	1	2	3
1	(1,2,1)	(2,1,3)	(3,2,2)
2	(3,1,3)	(2,1,2)	(2,1,3)

Providing An Integrated Multi-Depot Vehicle Routing Problem Model With Simultaneous...


The first segment of the chromosome is concerned with how the items are arranged in each package, considering that six varied dimensions are within each package. Consequently, each client generates three random numbers (1, 2, and 3). The x-axis is represented by the number 1, the y-axis by the number 2, and the z-axis by the number 3. For instance, the dimensions of product 2 for the client are 1 (2,1,3), meaning that the product is two units in length, one unit in breadth, and three units in height. Take chromosome 3-1-2, which was chosen at random for this product. Because the number 1 chromosome is recorded on the y-axis, this chromosome is taken to mean that the length of the final product must be along that axis. Because the number 2 chromosome is recorded on the x-axis, the product's width should be along that axis. Additionally, the product's height should be along the z-axis. As a result, Table 5 may be used to specify the chromosomal intended for Table 4.

Table 5. The first step initial solution

Customer	Product		
	1	2	3
1	1-2-3	2-1-3	3-2-1
2	1-3-2	1-3-2	1-2-3
			
1	(1,2,1)	(1,2,3)	(2,2,3)
2	(3,3,1)	(2,2,1)	(2,1,3)

Chromosome decoding requires the same procedure. The items of each client are first classified according to their maximum volume. Table 6 illustrates product volume sorting.

Table 6. Sort the volume of the products in the first step initial solution

Customer	Product		
	1	2	3
1	2	4	12
2	9	4	6
			
1	3	2	1
2	1	3	2

Following sorting, the lower-left corner of the box is put with the priority of customer 1, which is product 3, according to the altered measurements in Table 6. The first product is in package one, as seen in Figure 5.

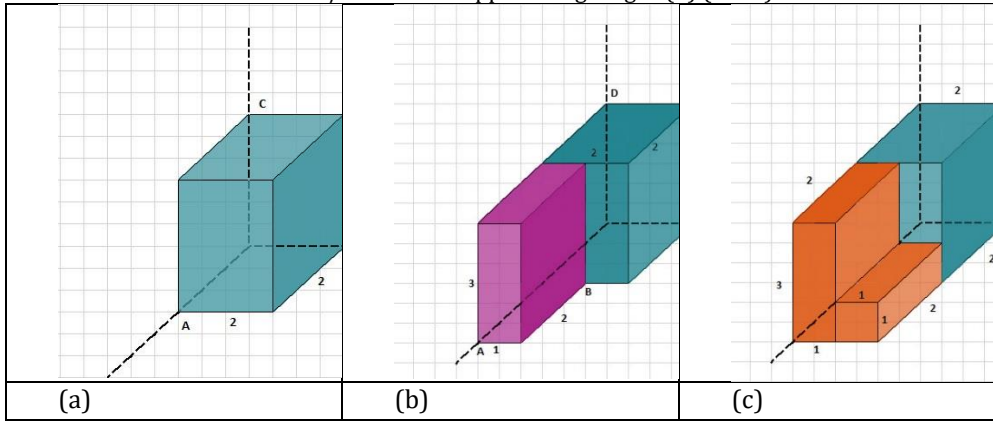


Figure 5. The example of the first product arrangement in the first step initial solution

Based on Table 6's priority, it can be shown from Figure 5(a) that 3 points, A, B, and C are eligible for the following product, i.e., product number 2. The SCA randomly chooses one of the valid sites to place the second product within the package. Figure 5(b) depicts the positioning of product 2. (for example, the SCA selects point A). Four additional positions, A, B, C, and D, will become eligible for the subsequent product when the second product is positioned on the length of the y-axis. The third product is arranged in this part using the SCA, which randomly chooses one of four acceptable places (such as B). The positioning of the third product in package number 1 is seen in Figure 5(c). The ideal length, width, and height values are established once all the items have been placed within the package; for example, the ideal closed dimensions for customer 1 are $3 * 4 * 2$ longitudinal units.

The second modeling stage aims to identify prospective distribution locations and VRP after reaching the ideal dimensions of items to be delivered to the consumer. To create the Pareto front, NSGA II and MOALO are employed. The basic chromosome is therefore shown in this section following Table 7, assuming five clients, three central warehouses, and one central warehouse. The designed chromosome may alternatively be divided into two sections, depending on the problem. Natural numbers are replaced for the total number of clients in the first level of the supply chain network and the total number of distribution centers in the second level.

Table 7. The initial solution to the problem

Initial Solution (Step 1)	5	3	4	2	1
Initial Solution (Step 2)	1		3		2

The assignment of clients to each of the distribution centers is the next step in the chromosomal design process. As a result, the total number of clients is randomly allocated to the total number of distribution centers. The vehicle's routing is determined by the numbers produced by the first level of the chromosome's initial response. On the chromosome in Figure 6, Table 8 depicts how consumers are allocated to distribution facilities and VRP.

Table 8. Decoding of the initial solution to the problem

Initial Solution (Step 1)	5	3	4	2	1
Initial Solution (Step 2)	1	3	2		

Customers five and three are assigned to distribution center 1, customer four is assigned to distribution center 3, and customers two and one are designated to distribution center 2. This is shown in Figure 7. Additionally, VRP from distribution centers 1, 3, and 2 is $L1 \rightarrow C5 \rightarrow C3 \rightarrow L1$, $L1 \rightarrow C5 \rightarrow C3 \rightarrow L1$, and VRP from distribution center 2 is $L2 \rightarrow C2 \rightarrow C1 \rightarrow L2$. Other problem limitations are then sequentially explored after allocating clients to distribution locations. The penalty function governs the limitation if the problem does not satisfy certain criteria.

5. Analysis of the Results

First, a small numerical example has been designed to analyze the problem, and the effectiveness of meta-heuristic algorithms compared to exact methods has been investigated. In the second part of the analysis of the results, a real study problem has been presented in Etko Broadcasting Company.

5.1. Small Size Sample Problem

This section examines a sample problem with three distribution facilities, six end users, two goods, and four vehicles to evaluate the developed model's performance. Table 9 provides a thorough breakdown of the issue parameters' range restrictions in accordance with the uniform distribution function.

Table 9. Problem parameters based on uniform distribution

Parameter	Parameter Range Limits	Parameter	Parameter Range Limits
U_l	$\sim U(10000,12000)$	$Tr_{nn'}$	$\sim U(30,40)$
F_v	$\sim U(300,400)$	$T_{nn'}$	$\sim U(15,20)$
D_{cp}	$\sim U(20,30)$	S_c	$\sim U(2,5)$
R_{cp}	$\sim U(10,15)$	C_{lp}	$\sim U(2,3)$
$CapV_v$	$\sim U(100,120)$	$[AS_c, BS_c]$	$\sim U(20,50)$
$CapL_{lp}$	$\sim U(200,220)$	α	6
$Dis_{nn'}$	$\sim U(10,100)$	H	3

Considering the two-stage model presented in this article, firstly, by using GAMS software and SCA, the dimensions of packages that can be sent to customers have been optimized. Each package contains two products; the optimal dimensions of each package are shown in Table 10.

Table 10. Packages Dimensions that can be delivered to customers in the first stage

Package	Customer	GAMS			SCA		
		Length	Width	Height	Length	Width	Height
1	1	12.26	4.39	5.27	4.39	5.27	12.26
2	2	11.67	4.66	4.19	4.66	11.67	4.19
3	3	11.96	4.76	5.67	5.67	4.96	10.94
4	4	4.03	11.67	5.03	5.03	12.01	4.12
5	5	4.68	12.37	4.87	4.69	4.87	12.37
6	6	12.25	5.03	5.22	5.24	5.26	12.40

The optimal value of the objective function obtained by GAMS software was equal to 563.26 units in 49.37 seconds. Meanwhile, the objective function obtained by the SCA in 5 executions and 150 consecutive iterations was 564.39 units in 12.18 seconds. By comparing the relative difference of the objective functions obtained from the first stage, it can be seen that the SCA has reached the objective function value with a difference of 0.2 in a much shorter period. The convergence of the SCA in 5 executions to achieve the near-optimal value is shown in Figure 6.

After determining the optimal dimensions of each package that can be sent to customers by different solution methods, selecting warehouses and choosing the optimal route for transporting products to customers by different vehicles have been discussed in the second stage. In this step, NSGA II, MOALO, and the precise LP metric method have been used. Due to the uncertainty of the value of delivery, pickup, and transfer cost parameters, the value of uncertainty rate $\rho=0.5$ has been used to determine the Pareto front. Based on this, the different efficient solutions obtained from other solution methods are shown in Table 11, and the Pareto front is formed in the numerical example in Figure 7.

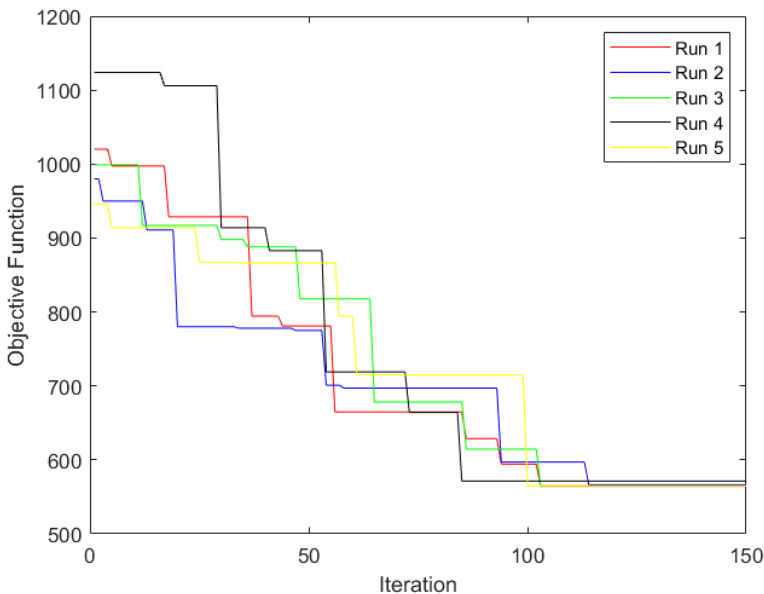


Figure 6. Convergence of SCA in solving the model

Table 11. Efficient solutions obtained in small size

Efficient Solution	LP-Metrics			NSGA II			MOLAO		
	W1	W2	W3	W1	W2	W3	W1	W2	W3
1	1316	5816	176.	13270.	63551.	180.	13380.	59898.	192.
	5.18	7.16	23	87	23	83	83	32	46
2	1321	5615	168.	13474.	62655.	180.	13383.	57913.	187.
	9.23	6.64	45	50	07	51	91	57	62
3	1349	4315	163.	13522.	61422.	176.	13423.	57415.	187.
	8.57	7.76	89	23	64	20	61	60	55
4	1381	3816	159.	13967.	60862.	175.	13467.	53725.	184.
	2.50	3.91	97	27	22	60	10	25	65
5	1403	3723	152.	14098.	52432.	174.	13551.	52534.	182.
	5.64	6.46	65	63	80	95	35	91	42
6	1426	3529	144.	14113.	49686.	167.	13707.	51729.	180.
	8.90	7.38	31	63	29	33	26	72	98
7	1452	3132	141.	14318.	48810.	164.	13880.	51630.	180.
	8.16	6.26	54	24	84	19	68	88	78
8	1461	3015	136.	14494.	43783.	161.	14033.	51519.	177.
	7.03	6.17	78	24	28	64	04	19	10
9	1498	2916	130.	14824.	43253.	160.	14579.	51347.	175.
	7.15	5.64	23	89	97	39	25	62	68
10	1507	2816	129.	14932.	42697.	154.	14672.	50219.	174.
	3.27	5.66	25	54	88	28	80	92	13
11	1525	2798	128.	15050.	37433.	150.	14806.	48745.	169.
	6.64	4.03	39	19	35	34	62	92	50
12	-	-	-	15422.	37411.	147.	14937.	46763.	162.
	-	-	-	48	35	81	21	34	88
13	-	-	-	15623.	36321.	143.	14973.	46000.	162.
	-	-	-	84	39	92	82	93	34
14	-	-	-	16366.	32899.	135.	15371.	45261.	160.
	-	-	-	94	92	66	14	15	74
15	-	-	-	16709.	32211.	130.	15743.	43550.	159.
	-	-	-	05	05	86	08	06	23
16	-	-	-	-	-	-	15983.	42357.	140.
	-	-	-	-	-	-	11	25	36
17	-	-	-	-	-	-	16078.	40013.	139.
	-	-	-	-	-	-	74	85	74
18	-	-	-	-	-	-	16124.	34029.	134.
	-	-	-	-	-	-	52	38	72
19	-	-	-	-	-	-	16387.	32778.	131.
	-	-	-	-	-	-	76	17	17

Table 11 shows that the comprehensive benchmark method has 11 effective solutions, the NSGA II has 15 effective solutions, and the MOALO has obtained 19 effective solutions. Also, by examining each of the effective solutions, it can be said that with the increase in the costs of the entire network, including the construction of more warehouses, the distance between the warehouses and customers will decrease, and this will lead to a decrease in the number of CO₂ emissions. As a result, a reduction of the number of working hours of drivers due to The distance traveled is reduced.

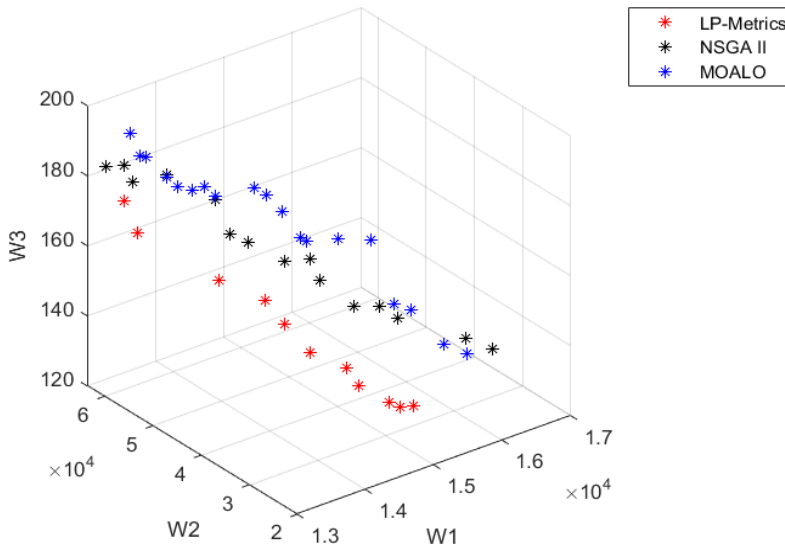


Figure 7. Pareto front obtained from solving the numerical example with different solution methods

Due to the difference in effective solutions obtained from each method and the impossibility of comparing two by two effective solutions, the comparison indexes of effective solutions have been used. Figure 8 shows the set of indicators obtained from solving the numerical example.

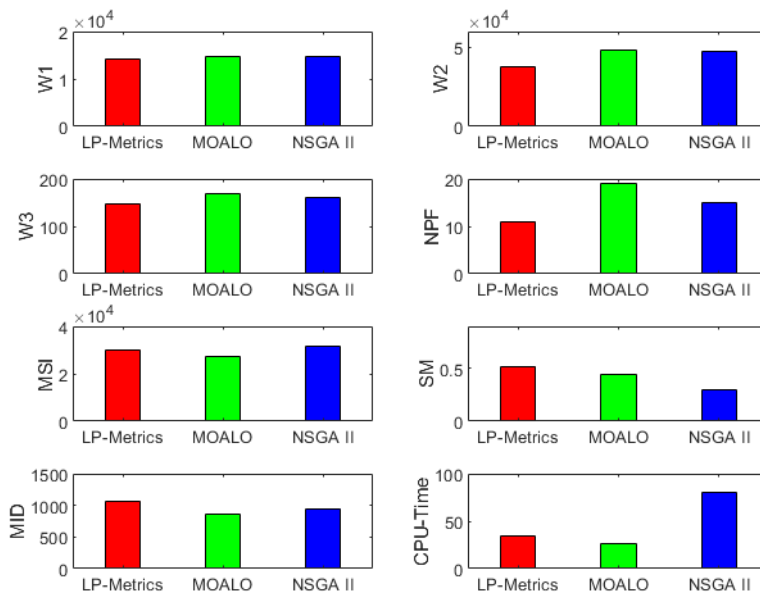


Figure 8. Indicators of comparison of effective solutions between different solution methods in solving the numerical example of the second stage

Because it is accurate, the LP metric approach acquired the lowest average values of the target functions, shown in Figure 8. This can be observed by referring to the findings that are presented there. Finally, the MOALO has obtained favorable results in getting the NPF, MID, and computing time. The NSGA II has obtained better results in obtaining the indicators of MSI and SM, and the MOALO has obtained favorable results in obtaining these three metrics. The TOPSIS was utilized to select the solution method that proved the most effective in getting various indicators. This was done because each solution method demonstrated its efficacy in obtaining its unique indicator. The findings of this approach indicated that the MOALO scored 0.6182, and the NSGA II scored 0.3818. As a result, the MOALO is displayed as the most effective approach for the proposed model's solution when applied to larger sizes.

5.2. Problem Sensitivity Analysis

When the values of the problem's parameters are altered, the problem's objective functions and output variables also experience shifts in their respective values. This is because the values of the problem's parameters are intertwined. Therefore, it is vital to examine their influence on the objective functions by modifying the various factors of the issue and seeing how this affects the objective functions. The value of $\alpha=0.5$ was utilized to manage the parameters because of the indeterminacy of the mathematical model and the use of the novel FRBO approach. Both of these factors contributed to the development of the method. As a result, it is essential to ascertain the impact of the shift in the uncertainty rate on the objective functions to solve it.

Consequently, the impact of the uncertainty rate on the delivery amount, the effect of the uncertainty rate on the pickup amount, and its simultaneous effect on the SPD amounts were investigated. The findings are shown in Figures 9 and respectively 11. Assuming a rise in the rate of uncertainty in the total quantity of delivery and pickup simultaneously, Figure 11 shows: The effect of the uncertainty rate on the values of the objective functions shown in Figures 10 and 11, respectively. In Figure 10, the authors assume an increase in the uncertainty rate in the delivery amount while assuming that the pickup amount will remain constant. In Figure 11, the authors consider increasing the uncertainty rate in the pickup amount while thinking that the delivery amount will remain constant.

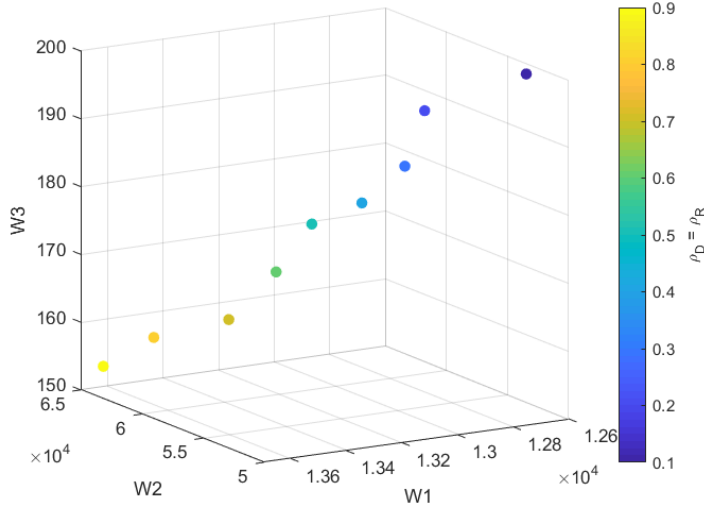


Figure 9. Sensitivity analysis on simultaneous changes in delivery and pickup amount

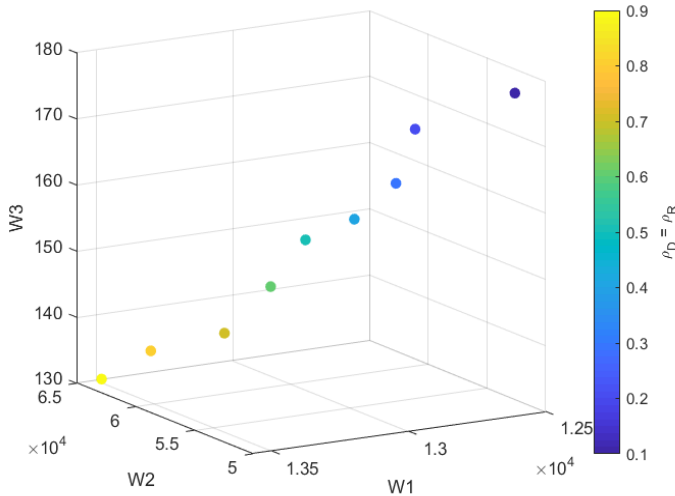


Figure 10. Sensitivity analysis on changes in the delivery amount and harvest stability

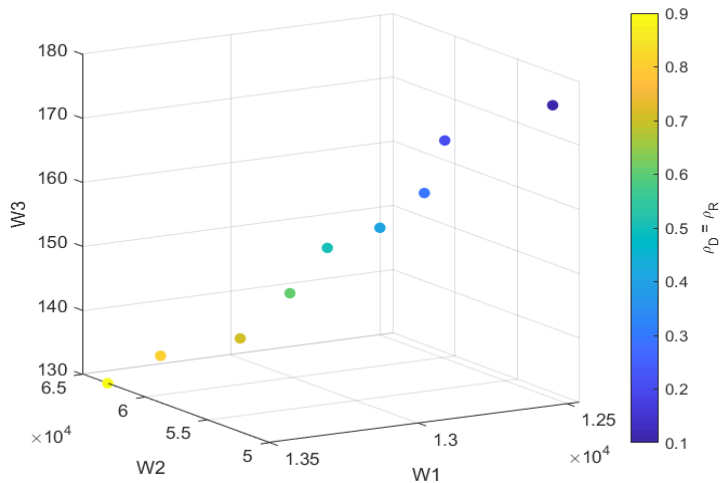


Figure 11. Sensitivity analysis on simultaneous changes in pickup amount and delivery stability

According to the findings presented in Figures 9 to 11, it is clear that as the rate of uncertainty rises as a consequence of an increase in the number of deliveries and pickups, and as the capacity of distribution centers and vehicles remains the same, there is a growing demand for an increase in the number of vehicles used for transportation, which in turn results in an increase in both the cost of transportation and the amount of gas emissions. It has been converted into a greenhouse. In addition, due to the rise in the number of cars, the total number of hours spent in vehicles has reduced, which correlates negatively with the increase in uncertainty. It shows the effect of the uncertainty rate on the values of the objective functions in Figures 9, 10, and 11, where Figure 9 assumes an increase in the uncertainty rate in the amount of delivery and withdrawal at the same time; Figure 10 assumes an increase in the uncertainty rate in the delivery amount, and the constancy of the withdrawal amount; and Figure 11 takes an increase in the uncertainty rate in the withdrawal amount and an endurance in the delivery amount. All of these figures are based on the assumption that the uncertainty

Table 12. General information about the problem

Number	
Periods	Twelve months from 2019 are included in the total number of periods for solving the problem.
Suppliers	Forty-seven firms provide the goods of Golrang Broadcasting Company.
Distribution Centers	There are 12 major distribution facilities for Golrang Broadcasting Company spread throughout the nation's regions. Only Tehran's sales distribution hub has been considered in this concept.
Customer Clusters	The demand regions are chosen in ten clusters adjacent to one another due to the limitations of the sales distribution center.
Products	Due to the Golrang Broadcasting Company's overwhelming product selection, 76 goods in 27 groups were chosen for this

project based on the highest sales (90%) and were then utilized to solve the model.

Transport Fleets	According to information from 2019, the firm owns 2 Isuzu and 2 Alvand vehicles, while 6 Nissan and 1 Isuzu vehicle.
------------------	--

5.3. Case Study

It is a case study that Etka Holding conducted. It is made up of a collection of businesses that are involved in manufacturing and distribution. Safir Etka Broadcasting Company is a connection between Etka Group's manufacturing firms and its merchants. This position is one of the most significant and critical roles the company performs among these other companies, each with its objective. When implemented in this firm, this article will result in a dependable and comprehensive optimization of the set of processes associated with this company. This optimization will finally clarify the procedures and the existing situation, ultimately leading to improved efficiency and reduced expenses. The results of this article can potentially empower this company, which plays an essential role in the overall complex. Considering the novelty of this project in the country, it has the potential to put it in a better position. This is in consideration of the current competitive conditions, which are becoming more sensitive daily due to the liberalization of economic borders. Supplied for this business compared to those offered by local and international rivals. Table 12 provides a portion of the data required to address the challenge posed by the real-world case study.

After applying the MOALO to the abovementioned issue, 13 effective solutions were produced in 276.26 seconds. This result represents the Pareto front, and the practical solutions are detailed in the following paragraphs.

Table 13. Efficient solutions obtained from solving the real sample problem

Efficient Solution	OBF1 (100000*)	OBF2	OBF3
1	21920.63	129940.23	8.30
2	22632.01	128806.47	8.49
3	25190.37	122321.32	8.69
4	25302.38	108496.39	8.92
5	27860.78	101477.99	9.3
6	28053.16	94947.19	9.38
7	30659.45	88979.58	9.56
8	30663.61	77378.16	9.68
9	31358.32	76578.61	9.90
10	31424.17	76122.87	10.11
11	32232.88	75166.32	10.71
12	36740.21	73320.94	10.82
13	37627.15	67119.05	10.94

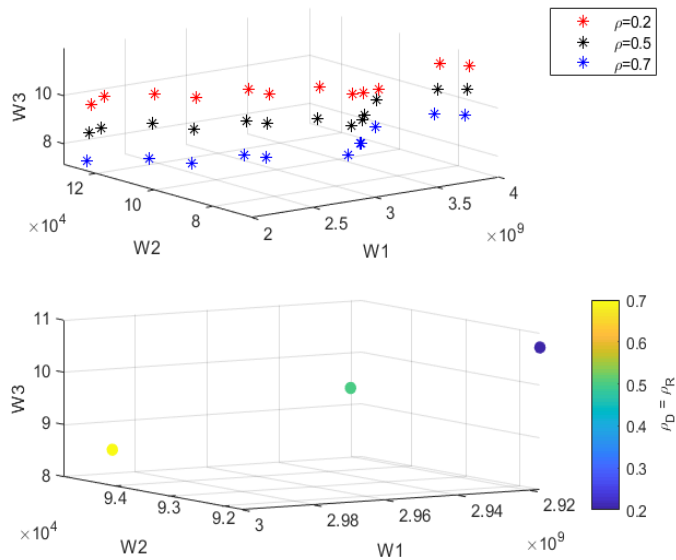


Figure 12. Pareto front obtained from solving the real study at different rates of uncertainty

The efficient solution obtained from Table 13 has been checked at the uncertainty rate of $\rho=0.5$. Therefore, Figure 12 examines the Pareto front obtained at different uncertainty rates.

6. Conclusion and Future Suggestions

While focusing on the fact that environmental concerns and reducing fuel consumption are seen as fundamental goals for the global community, and even though in observing the records, mainly separately and in some cases, the combination of some items, there is no history of integrated research concerning environmental concerns and reducing fuel consumption, the issue of vehicle routing plays a significant role in logistics and its supply chain at the operational levels as of. It consists of a group of companies engaged in production and distribution. The Safir Etko Broadcasting Company links the merchants and the industrial companies of the Etko Group. Among these different businesses, each of which has its own goal, this one plays one of the most vital functions for the organization. An accurate and thorough optimization of the processes related to this organization has been achieved thanks to the implementation of this research in this corporation. This optimization will eventually clarify the procedures and situation, ultimately enhancing efficiency and saving costs. Given the importance of this company's function in the whole complex and the fact that this strategy is relatively new to the nation, it has the potential to put it in an increasingly advantageous position. These arguments are pertinent given the current competitive environment, which is becoming more delicate daily as economic boundaries are opened. In this article, a mathematical model of truck routing with simultaneous delivery and pickup with several warehouses is suggested for Safir Broadcasting Company in contrast to those provided by local and

worldwide competitors. The Safir Broadcasting Company is the intended use of this model, which is divided into two stages: the first stage discusses the location of potential product distributor warehouses and the best transportation routing for these products using different vehicles, and the second stage deals with the arrangement of goods and products inside vehicles. The goal of the objective functions that will be presented in this article's first stage is to optimize package dimensions, and the purpose of the objective functions that will be shown in the second stage is to simultaneously minimize the costs of routing and location, the amount of greenhouse gas emissions, and the maximum driving time.

In conclusion, this study discusses NSGA II, MOALO, and SCA. The model of a larger scale is solved using these approaches (case study). According to the study's results, there is a link between rising rates of uncertainty and higher prices and amounts of greenhouse gas emissions, as well as a decline in the number of hours drivers put in at work due to rising rates of uncertainty. Demand is at its highest in a gloomy scenario, which increases the requirement for vehicles to transport goods and services. Therefore, the cost and volume of greenhouse gas emissions rise. The results show that the MOALO is better than the NSGA II technique when successfully addressing small-scale difficulties. This strategy was adopted to address the problem of the too-large size. There are thirteen workable solutions to the issue, according to the research into how it may be used on a larger scale (the Ettaka case study).

Authors contributions: M. K. contributed to conceptualization and methodology; S. E. N. helped with writing, reviewing, and editing; H. K. conducted analysis and provided input on methodology; and M. S. contributed to methodology and validation. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding

Data Availability Statement: The data used to support the findings of this study are included within the article.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

- Ahmadizar, F., Zeynivand, M., & Arkat, J. (2015). Two-level vehicle routing with cross-docking in a three-echelon supply chain: A genetic algorithm approach. *Applied Mathematical Modelling*, 39, 7065–7081. <https://doi.org/10.1016/j.apm.2015.03.005>
- Avcı, M., & Topaloglu, S. (2016). A hybrid metaheuristic algorithm for heterogeneous vehicle routing problem with simultaneous pickup and delivery. *Expert Systems with Applications*, 53, 160–171. <https://doi.org/10.1016/j.eswa.2016.01.038>
- Belgin, O., Karaoglan, I., & Altıparmak, F. (2018). Two-echelon vehicle routing problem with simultaneous pickup and delivery: Mathematical model and heuristic approach.

Providing An Integrated Multi-Depot Vehicle Routing Problem Model With Simultaneous...
Computers and Industrial Engineering, 115, 1–16.
<https://doi.org/10.1016/j.cie.2017.10.032>

Brandão, J. (2018). Iterated local search algorithm with ejection chains for the open vehicle routing problem with time windows. *Computers and Industrial Engineering*, 120, 146–159. <https://doi.org/10.1016/j.cie.2018.04.032>

Casazza, M., Ceselli, A., & Wolfler Calvo, R. (2021). A route decomposition approach for the single commodity Split Pickup and Split Delivery Vehicle Routing Problem. *European Journal of Operational Research*, 289, 897–911. <https://doi.org/10.1016/j.ejor.2019.07.015>

Curtois, T., Landa-Silva, D., Qu, Y., & Laesanklang, W. (2018). Large neighbourhood search with adaptive guided ejection search for the pickup and delivery problem with time windows. *EURO Journal on Transportation and Logistics*, 7, 151–192. <https://doi.org/10.1007/s13676-017-0115-6>

Dambakk, C. (2019). The Maritime Pickup and Delivery Problem with Cost and Time Window Constraints: System Modeling and A* Based Solution. Master's Thesis, Universitetet i Agder; University of Agder.

Dantzig, G. B., & Ramser, J. H. (1959). The Truck Dispatching Problem. *Management Science*, 6, 80–91. <https://doi.org/10.1287/mnsc.6.1.80>

Dell'Amico, M., Furini, F., & Iori, M. (2020). A branch-and-price algorithm for the temporal bin packing problem. *Computers and Operations Research*, 114, 104825. <https://doi.org/10.1016/j.cor.2019.104825>

do C. Martins, L., Hirsch, P., & Juan, A. A. (2021). Agile optimization of a two-echelon vehicle routing problem with pickup and delivery. *International Transactions in Operational Research*, 28, 201–221. <https://doi.org/10.1111/itor.12796>

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

Fu, Y., & Banerjee, A. (2020). Heuristic/meta-heuristic methods for restricted bin packing problem. *Journal of Heuristics*, 26, 637–662. <https://doi.org/10.1007/s10732-020-09444-y>

Hemmati Golsefidi, A., & Akbari Jokar, M. R. (2020). A robust optimization approach for the production-inventory-routing problem with simultaneous pickup and delivery. *Computers and Industrial Engineering*, 143, 106388. <https://doi.org/10.1016/j.cie.2020.106388>

Ghahremani-Nahr, J., Najafi, S. E., & Nozari, H. (2022). A Combined Transportation Model for the Fruit and Vegetable Supply Chain Network. *Journal of Optimization in Industrial Engineering*, 15, 131–145. <https://doi.org/10.22094/joie.2022.1948231.1925>

Hadian, H., Golmohammadi, A. M., Hemmati, A., & Mashkani, O. (2019). A multi-depot location routing problem to reduce the differences between the vehicle traveled distances; A comparative study of heuristics. *Uncertain Supply Chain Management*, 7, 17–32. <https://doi.org/10.5267/j.uscm.2018.6.001>

Kalayci, C. B., & Kaya, C. (2016). An ant colony system empowered variable neighborhood search algorithm for the vehicle routing problem with simultaneous pickup and delivery. *Expert Systems with Applications*, 66, 163–175. <https://doi.org/10.1016/j.eswa.2016.09.017>

Kara, İ., Kara, B. Y., & Yetis, M. K. (2007). Energy Minimizing Vehicle Routing Problem BT - Combinatorial Optimization and Applications. *International Conference on Combinatorial Optimization and Applications*, 4616, 62–71.

Kartal, Z., Hasgul, S., & Ernst, A. T. (2017). Single allocation p-hub median location and routing problem with simultaneous pickup and delivery. *Transportation Research Part E: Logistics and Transportation Review*, 108, 141–159. <https://doi.org/10.1016/j.tre.2017.10.004>

Koç, Ç., Laporte, G., & Tükenmez, İ. (2020). A review of vehicle routing with simultaneous pickup and delivery. *Computers and Operations Research*, 122, 104987. <https://doi.org/10.1016/j.cor.2020.104987>

Ky Phuc, P. N., & Phuong Thao, N. Le. (2021). Ant Colony Optimization for Multiple Pickup and Multiple Delivery Vehicle Routing Problem with Time Window and Heterogeneous Fleets. *Logistics*, 5, 28. <https://doi.org/10.3390/logistics5020028>

Lagos, C., Guerrero, G., Cabrera, E., Moltedo-Perfetti, Andr. S., Johnson, F., & Paredes, F. (2018). An improved particle swarm optimization algorithm for the VRP with simultaneous pickup and delivery and time windows. *IEEE Latin America Transactions*, 16, 1732–1740. <https://doi.org/10.1109/TLA.2018.8444393>

Li, J., Li, T., Yu, Y., Zhang, Z., Pardalos, P. M., Zhang, Y., & Ma, Y. (2019). Discrete firefly algorithm with compound neighborhoods for asymmetric multi-depot vehicle routing problem in the maintenance of farm machinery. *Applied Soft Computing Journal*, 81, 105–460. <https://doi.org/10.1016/j.asoc.2019.04.030>

Ma, Y., Li, Z., Yan, F., & Feng, C. (2019). A hybrid priority-based genetic algorithm for simultaneous pickup and delivery problems in reverse logistics with time windows and multiple decision-makers. *Soft Computing*, 23, 6697–6714. <https://doi.org/10.1007/s00500-019-03754-5>

Mirjalili, S. (2015). The ant lion optimizer. *Advances in Engineering Software*, 83, 80–98. <https://doi.org/10.1016/j.advengsoft.2015.01.010>

Mirjalili, S. (2016). SCA: a sine cosine algorithm for solving optimization problems. *Knowledge-Based Systems*, 96, 120-133.

Wang, M., & Lu, G. (2021). A Modified Sine Cosine Algorithm for Solving Optimization Problems. *IEEE Access*, 9, 27434–27450. <https://doi.org/10.1109/ACCESS.2021.3058128>

Nadizadeh, A., & Kafash, B. (2019). Fuzzy capacitated location-routing problem with simultaneous pickup and delivery demands. *Transportation Letters*, 11, 1–19. <https://doi.org/10.1080/19427867.2016.1270798>

Polyakovskiy, S., & M'Hallah, R. (2018). A hybrid feasibility constraints-guided search to the two-dimensional bin packing problem with due dates. *European Journal of Operational Research*, 266, 819–839. <https://doi.org/10.1016/j.ejor.2017.10.046>

Providing An Integrated Multi-Depot Vehicle Routing Problem Model With Simultaneous...
Sadati, M. E. H., Aksen, D., & Aras, N. (2020). The r-interdiction selective multi-depot vehicle routing problem. *International Transactions in Operational Research*, 27, 835-866.

Scheithauer, G. (2018). *Introduction to Cutting and Packing Optimization*. Springer, Cham., 263, 14. <http://link.springer.com/10.1007/978-3-319-64403-5>

Spencer, K. Y., Tsvetkov, P. V., & Jarrell, J. J. (2019). A greedy memetic algorithm for a multiobjective dynamic bin packing problem for storing cooling objects. *Journal of Heuristics*, 25, 1–45. <https://doi.org/10.1007/s10732-018-9382-0>

Ulmer, M. W., Thomas, B. W., Campbell, A. M., & Woyak, N. (2021). The restaurant meal delivery problem: Dynamic pickup and delivery with deadlines and random ready times. *Transportation Science*, 55, 75–100. <https://doi.org/10.1287/TRSC.2020.1000>

Zahedi, M. R., & Nahr, J. G. (2020). Designing a hub covering location problem under uncertainty conditions. *Decision Science Letters*, 9, 477–500. <https://doi.org/10.5267/j.dsl.2020.2.002>

Zhang, S., Zhang, W., Gajpal, Y., & Appadoo, S. S. (2019). Ant Colony Algorithm for Routing Alternate Fuel Vehicles in Multi-depot Vehicle Routing Problem. Springer, Singapore. In *Decision Science in Action*, 251–260. https://doi.org/10.1007/978-981-13-0860-4_19



© 2023 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).