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A Neutrosophic Fuzzy Programming Method to Solve a Multi-depot Vehicle Routing Model under Uncertainty during the COVID-19 Pandemic

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ABSTRACT

The worldwide prevalence of coronavirus disease (COVID-19) and the severe problems in the distribution of medical equipment have led to the modeling of multi-depot vehicle routing under uncertainty in the COVID-19 pandemic. The primary purpose of the proposed model is to locate warehouses and production centers and route vehicles for the distribution of medical goods to hospitals. A robust fuzzy method controls uncertain parameters, such as demand, transmission, and distribution costs. The effect of uncertainty using a neutrosophic fuzzy programming method shows that by increasing demand, the volume of medical goods exchanges and the number of vehicles used to distribute goods increase. This leads to an increase in the total cost of the problem and the amount of greenhouse gas (GHG) emissions. The results also show that using more vehicles reduces staff fatigue to distribute medical products and reduces the prevalence of the COVID-19 pandemic. In the most important sensitivity analysis of the problem on the capacity of the vehicle, it was determined that by increasing the capacity of the vehicle, fewer vehicles are used, and as a result, the cost and amount of greenhouse gas emissions are reduced. On the other hand, this has led to a decrease in the prevalence of the COVID-19 virus.

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1. INTRODUCTION

Logistics is a recognized science as a value-added activity for companies and their products and services by coordinating activities, such as materials management and management, optimizing resource use, minimizing costs, and maximizing service levels. In traditional systems, traffic flows are provided from one category of the supply chain to another. More flexible systems allow for relocation at one level, divide inventory between wholesalers and thus inventory, and manage costs without changing the level of service [1]. Logistics systems are emerging as an essential tool for competition and efficiency for companies to maintain sustainable business and achieve global scale [2]. Their primary purpose is to coordinate activities (e.g., transportation, order processing, warehousing, inventory management, and maintenance) designated as inventory management. Along with the level of services, the total logistical cost of these activities has become one of the most important economic indicators for the efficiency of a supply chain [3]. In 2014, logistics costs accounted for 11.2% of Brazilian companies' revenues. Vehicle routing and inventory management are essential for logistics systems that directly impact design costs [4].

Dantzig and Ramser [5] first proposed the problem of vehicle routing in 1959. This is a combination of the two issues of the traveling salesman (unlimited consideration of vehicle capacity) and the packing of boxes (zero consideration of freight costs on the ridges), trying to optimally design a set of routes for the transport fleet in such a way that a certain number of customers to be served and has different side restrictions [6]. The variety of this problem is so great that it is challenging and time-consuming to classify them and express the various states in which it occurs. Since its inception in the 1960s, many

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extensions have been derived based on their different applications in the real world as there are now versions, such as heterogeneous type [7], simultaneous receipt and delivery [8], open type [9], and others [10].

One of the factors is the application of this issue in the real world that has made the issue of vehicle routing as one of the most important issues of combinatorial optimization and has attracted the attention of many researchers. For example, suppose that a factory can reduce the length of time, on when it takes to deliver goods to its customers or the number of its vehicles and thus its cost [10, 11]. Therefore, by reducing the length of the delivery or receipt of goods, the company can provide better services to its customers by reducing the cost of goods and increasing delivery speed [12]. As a result, the company will increase its competitiveness against other similar companies, expand its product market, and ultimately make more profit [13]. In general, inventory and transportation are two important factors in the cost component [14]. This shows why companies and academic researchers are working so hard to find efficient and economical hybrid management systems for transportation and inventory. According to Anderson et al. [4], no commercial systems are available to support decisions about inventory management and vehicle routing issues simultaneously. In this regard, a recurring theme in recent research is the inventory-routing problem (IRP), which results from a combination of vehicle routing and inventory management.

The use of IRP models allows the simultaneous determination of the optimal level of inventory, delivery routes, and vehicle schedules based on the minimum cost criterion. Guemri et al. [15] considered minimizing distribution and inventory costs as the goals of the IRP. They also mentioned some components, including the vehicle and the storage capacity of the facility. According to Coelho et al. [16], scientific research on the IRP is relatively new than optimization issues, such as vehicle routing problems (VRP). They also noted that although several studies have reviewed the literature on inventory management and routing issues, relatively few have examined the integration of these two issues. Inventory systems are hierarchical, with traffic flowing from one floor of the supply chain to another, from manufacturers to wholesalers, and then from wholesalers to retailers. More flexible systems allow for lateral transportation on one level (i.e., between wholesalers or retailers). In this case, members of the same category can share their inventory, which allows them to reduce the inventory level while ensuring some of the required level services. When transport is included, the problem is defined as IRP with transportation (IRPT) [17].

The importance of a multi-depot VRP has led to the inventory discussion leading to the design of a new model under uncertainty under the COVID-19 pandemic. Today, due to the presence of COVID-19, the transportation of products, especially medical equipment, is of the greater importance, and researchers are seeking to provide models to reduce vehicle traffic to reduce congestion and the spread of COVID-19. Considering the stability aspects of the model in the COVID-19 pandemic conditions has led to the design of a multi-depot vehicle routing model consisting of production centers, warehouses, and hospitals. The most important decisions taken in this issue include locating warehouses and production centers, optimal routing of medical equipment transportation to hospitals, determining the optimal amount of inventory in warehouses. Since the demand for medical goods in the pandemic conditions of COVID-19 is very variable, the robust fuzzy method is used to control the demand parameters, transmission, and distribution costs.

The remaining structure of this paper is as follows. Section 2 reviews the research literature and determines the research gap. In Section 3, a model of the VRP is presented several times, and the fuzzy parameters of the problem are controlled using the robust fuzzy method. Section 4 describes the neutrosophic fuzzy programming method as a tri-objective model solution. In section 5, a numerical example and its sensitivity are analyzed. Finally, in section 6, the conclusions of the model and solution method are presented.

2. LITERATURE REVIEW

The importance of vehicle routing has extensively been studied in recent decades with various developments and solutions. One of the areas considered recently in the routing issue is the green VRP, whose objective is to route vehicles considering the effects of the environment and fuel consumption [18]. Sustainable vehicle routing issues are divided into three general routing branches: optimized fuel consumption, environmental pollution, and logistics. In the routing field with optimization of fuel consumption, a model minimization of energy consumption in the VRP was presented. The objective function presented in this model was the product of the distance traveled in the vehicle's total weight, including the weights of the vehicle and cargo [19]. In addition to the distance traveled and the total weight, the vehicle speed was studied to calculate the fuel consumption in the time-dependent VRP and solved using the refrigeration simulation algorithm. Of course, a mathematical model for the problem was not presented [20].

Xiao et al. [21] considered a capacity routing problem in the distribution of goods minimizing fuel consumption and used a refrigeration simulation algorithm. The problem of cross-docking two-tier vehicle routing in a three-tier supply chain includes suppliers, cross-dock, and retailers. Two levels (i.e., suppliers and cross-docks) of network routing are considered and solved by the genetic algorithm (GA) and local search method [22]. The open VRP uses cross storage while comparing the results of CPLEX and refrigeration simulation algorithm [23]. Lalla-Ruiz et al. [24] proposed a new mathematical model for the multi-depot VRP by adding further limitations to previous papers. The computational results obtained from the sample problems showed the high efficiency of the mathematical model. Du et al. [25] developed a fuzzy linear programming model to minimize the risk of expected transportation when preparing hazardous materials and transporting products from different warehouses to customers. To solve the problem, four meta-innovative algorithms (i.e., GA, particle swarm optimization, refrigeration simulation, and ant colony optimization) were used, and comparisons were made between the proposed algorithms by providing numerical examples.

Alinaghian and Shokouhi [26] presented a mathematical model to solve the reservoir routing problem. The objective function of this model was to minimize the number of vehicles and then minimize the distance between the total routes traveled. Each vehicle's cargo space has several sections; each tank is assigned to one type of product. They used a hybrid algorithm to solve the model and compared the obtained results with the results of the exact method, which concluded that the hybrid algorithm presented by them has high efficiency in problem-solving. Brandao [27] designed an open VRP with a time window in mind and used an iterative local search algorithm to solve it. This algorithm was used for larger size data and was implemented on a total of 418 sample problems. The results showed the high efficiency of this algorithm in solving larger-sized problems. Polyakovskiy et al. [28] examined and modeled the product layout problem in two-dimensional space. For this purpose, they presented a mixed-integer linear programming (MILP) model and solved the model in small sizes by CPLEX software. They also used innovative algorithms to solve problems in larger sizes. Ghahramani et al. [29] implemented a new fuzzy method in a closed-loop supply chain (CLSC) network, including locating potential facilities and optimally allocating product flows. They used the whale optimization algorithm to solve their model and showed that the efficiency of the proposed algorithm is higher than the existing algorithms. Li et al. [30] determined the optimal location of warehouses and vehicle routing. They used the firewall algorithm to solve the problem. Sadati et al. [31] presented a skeleton game to determine the optimal location of warehouses and vehicle routing to reduce costs. In the first and second levels, the decision-maker as the leader chooses the facility's optimal location and determines the vehicles' optimal route, respectively. Mojtahedi et al. [32]. Developing a sustainable vehicle routing problem considering different fleet sizes for coordinated solid waste management.

Zhang et al. [33] considered a multi-depot green VRP and proposed an ant colony algorithm to solve the problem. In their study, a significant limitation is the vehicle capacity added to the model to make it more meaningful and closer to the real world. Dell Amico et al. [34] solved their model by the branch-and-price algorithm and examined their problem under various problems. Mirzaei and Seifi [35] considered the IRP for perishable goods and proposed a combined algorithm of tabu search of simulated annealing to solve large-sized problems. Soysal et al. [36] proposed an IRP model for perishable products based on environmental impacts and uncertainty demand. This model was confirmed through a case study of a fresh tomato supply chain. Nunes Bezerra et al. [37] proposed a location-inventory model for a CLSC and considered an integer nonlinear programming model under some constraints. Guimarães et al. [38] minimized the loss of the IRP using a GA. Chen et al. [39] modeled a VRP to distribute food among residents under COVID-19 conditions. They used the PEABCTS algorithm to solve the problem. Xu et al. [40] proposed a mixed-integer linear programming model to optimize the routing problem of the benzene emergency distribution vehicle by considering the time window. They used a particle swarm optimization algorithm to solve the problem. Ghiyasvand et al. [41] modeled and solved the home health care routing and scheduling problem with public and private transportation modes. The objective minimizes the total travel distance and overtime costs. They used three algorithms (i.e., IWO, GOA, and SA) to solve their problem.

Saffarian et al. [2] developed a hybrid genetic-simulated annealing-auction algorithm for a fully fuzzy multi-period multi-depot vehicle routing problem. The obtained results showed that the algorithm provides satisfactory results in terms of different performance criteria. Salamati [42] considered an Integrated Neutrosophic SWARA and VIKOR method for ranking risks of green supply chain. Fallah and Nozari [43] used neutrosophic mathematical programming for optimization of multi-objective sustainable biomass supply chain network design. By examining the rate of uncertainty, it was observed that with increasing this rate, the total costs of supply chain network design, greenhouse gas emissions, and product transfer times have increased. In contrast, the potential employment rate of individuals has decreased. Islam et al [44] introduced a novel particle swarm optimization-based grey model to predict warehouse performance. Beiki et al [45] developed a multi-objective model as a multi-vehicle relief logistic problem considering satisfaction levels by concerning the environmental conditions paying attention to uncertainty. To solve the problem, an exact solver by using the epsilon-constraint method is conducted to validate the model. Fallahtafti et al [46] proposed a two-echelon location routing framework for cash-in-transit. To mitigate the risk of robbery in cash transportation, a dynamic risk index is considered. The case study is researched in more depth to obtain managerial insights. The results show that depending on the risk or cost efficiency of the solutions on a Pareto frontier, the risk of traversing longer routes or transporting more significant amounts of cash can be determined in locating new bank vaults.

By examining the literature, some researchers have modeled the multi-depot VRP, each of which has unique characteristics. Therefore, considering the comprehensiveness of the model, the main features of the present paper can be summarized as follows:

- Considering the sustainability in the multi-depot VRP in COVID-19 pandemic conditions.
- Using the neutrosophic fuzzy programming method to solve the problem.
- Using the robust fuzzy method to control demand, transfer, and operating costs.

3. PROBLEM DEFINITION AND MODELING

According to Figure 1, this paper presents a multi-depot vehicle routing model for distributing essential medical supplies to hospitals under the COVID-19 pandemic. Accordingly, the main goal is to make integrated strategic and tactical decisions for the location of warehouses and the routing of the vehicle for the distribution of medical goods. According to this figure, as the last level of the supply chain, several hospitals have different demands for essential medical goods in different periods. Each warehouse has a level of inventory capacity that, after receiving the demand of hospitals, distributes medical goods to hospitals based on its inventory. Each hospital has a time window to receive essential medical supplies. This is due to the reduced traffic for the outbreak of the COVID-19 virus. In case of a shortage of inventory, the warehouses send their order for production to the production centers.

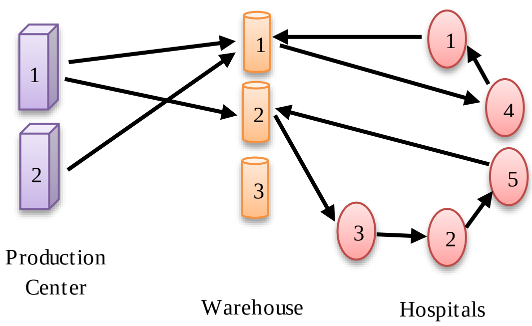

Figure 1. Multi-depot vehicle routing network

In this paper, in addition to the objective function of reducing the costs of location, routing and inventory of goods, the economic and social aspects are also addressed (i.e., minimizing greenhouse gas emissions and reducing the maximum working hours of drivers). Therefore, the timely delivery of medical goods according to a difficult time window leads to social distance, and the prevalence of the COVID-19 virus is reduced due to reduced driver density. Considering the mentioned aspects in problem modeling will lead to the closeness of the model to the real world, given that the multi-depot vehicle routing model is considered in sustainable conditions. Therefore, in one of the objective functions, the environmental aspect is discussed. Hence, minimizing greenhouse gas emissions as an environmental aspect has been proposed as an objective function in the problem. According to the definition of the above problem, the multi-depot VRP can be modeled according to the following assumptions:

- It is a multi-period and multi-product model.
- The number and location of hospitals are fixed and known in advance.
- All the capacity of production centers and warehouses is known and specified.
- A difficult time window is set for the distribution of essential medical supplies.
- Medical goods are transported from a production center to hospitals to minimize pollution with identical vehicles.
- Demand parameters, transmission costs, and distribution costs are considered indefinitely, and fuzzy triangular numbers are considered.

In the following, according to the problem assumptions, the symbols used in problem modeling are described. These symbols include model sets, parameters, and decision variables.

3. 1. Sets

K	Set of production centers
L	Set of warehouses
C	Set of hospitals
P	Set of medical goods
T	Period set
V	Set of vehicles

3. 2. Parameters

H_k	Cost of establishing warehouse k
U_l	Cost of establishing distribution center l
F_v	Fixed cost of using vehicle v
$\tilde{T}_{k,l,v}$	The cost of transportation between production center k and warehouse l by vehicle v
$\tilde{T}_{l,c,v}$	The cost of transportation between warehouse l and hospital c by vehicle v $l, c \in L \cup C$

$Co2_{k,l,v}$ The amount of greenhouse gas emissions in the movement of vehicle v between production center k and warehouse l

$Co2_{l,c,v}$ The amount of greenhouse gas (GHG) emissions in the movement of vehicle v between warehouse l and hospital c $(l, c \in L \cup C)$

$Ti_{l,c,v}$ Transportation time between warehouse l and hospital c by vehicle v $(l, c \in L \cup C)$

$H_{l,p}$ The cost of maintaining each unit of medical goods p in warehouse l

$\tilde{C}_{l,p}$ Cost of distribution per unit of medical goods p by warehouse l

$\widetilde{Dem}_{c,p,t}$ Hospital c demand for medical goods p in period t

$CapK_{k,p}$ Maximum capacity of the production center k of the production of medical goods p

$CapL_{l,p}$ Maximum capacity of warehouse l of storage and distribution of medical goods p

Cap_v Maximum capacity of vehicle v

$[AH_c, BH_c]$ Hard time window for delivery of medical goods to hospital c

3. 3. Decision Variables

$X_{k,l,p,t}$ Amount of medical goods p transferred between production center k and warehouse l in period t

$V'_{l,p,t}$ The total amount of medical goods p transferred from warehouse l in period t

$Q_{l,p,t}$ Inventory level of medical goods p in stock l in period t

Z_k 1 if production center k is established; 0, otherwise

Z_l 1 if warehouse l is established; 0, otherwise

Z_v 1 if vehicle v is used; 0, otherwise

$Y_{l,c,t}$ 1 if hospital c is allocated to warehouse l in period t; 0, otherwise

$Z_{l,c,v,t}$ 1 if hospital c is visited by vehicle v in period t after warehouse l; 0, otherwise $(l, c \in L \cup C)$

$U_{c,v,t}$ Auxiliary variable for sub-tour remove constraint

$R_{k,l,v,t}$ 1 if the route between production center k and warehouse l is visited by vehicle v in period t; 0, otherwise

$Tc_{l,c,v,t}$ Time of arrival of vehicle v to hospital c and out of warehouse l in period t

$Tw_{l,v,t}$ Maximum working hours of the driver of vehicle v who leaves warehouse l in period t

3. 4. Multi-depot VRP Model Given the expression of the sets, parameters, and decision variables expressed, the multi-depot VRP under the COVID-19 pandemic as a mixed-linear programming model is as follows:

$$\text{Min } \omega 1 = \sum_{k=1}^{K} H_k Z_k + \sum_{l=1}^{L} U_l Z_L + \sum_{v=1}^{V} F_v Z_v + \sum_{l=1}^{L\cup C}\sum_{c=1}^{L\cup C}\sum_{v=1}^{V}\sum_{t=1}^{T} \tilde{T}_{l,c,v} Z_{l,c,v,t} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{v=1}^{V}\sum_{t=1}^{T} \tilde{T}_{k,l,v} R_{k,l,v,t} + \sum_{l=1}^{L}\sum_{p=1}^{P}\sum_{t=1}^{T} H_{l,p} Q_{l,p,t} + \sum_{l=1}^{L}\sum_{p=1}^{P}\sum_{t=1}^{T} \tilde{C}_{l,p} V'_{l,p,t} \quad (1)$$

$$\text{Min } \omega 2 = \sum_{l=1}^{L\cup C}\sum_{c=1}^{L\cup C}\sum_{v=1}^{V}\sum_{t=1}^{T} Co2_{l,c,v} Z_{l,c,v,t} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{v=1}^{V}\sum_{t=1}^{T} Co2_{k,l,v} R_{k,l,v,t} \quad (2)$$

$$\text{Min } \omega 3 = max\{TW_{l,v,t}, \quad \forall l \in L, v \in V, t \in T\} \quad (3)$$

s. t.

$$\sum_{c=1}^{C}\sum_{l=1}^{C\cup L}\sum_{p=1}^{P} \widetilde{Dem}_{c,p,t} Z_{l,c,v,t} \le Cap_v Z_v, \quad \forall v,t \quad (4)$$

$$V'_{l,p,t} = \sum_{c=1}^{C}\sum_{v=1}^{V} \widetilde{Dem}_{c,p,t} Z_{l,c,v,t}, \quad \forall l,p,t \quad (5)$$

$$\sum_{v=1}^{V}\sum_{l=1}^{C\cup L} Z_{l,c,v,t} = 1, \quad \forall c,t \quad (6)$$

$$Q_{l,p,t} = \sum_{k=1}^{K} X_{k,l,p,t} + Q_{l,p,t-1} - V'_{l,p,t}, \quad \forall l,p,t \quad (7)$$

$$U_{m,v,t} - U_{c,v,t} + |C| Z_{m,c,v,t} \le |C| - 1, \quad \forall m,c \in C, v, t \quad (8)$$

$$\sum_{c=1}^{C\cup L} Z_{l,c,v,t} = \sum_{c=1}^{C\cup L} Z_{c,l,v,t}, \quad \forall v,t,l \in C \cup L \quad (9)$$

$$\sum_{l=1}^{L}\sum_{c=1}^{C} Z_{l,c,v,t} \le 1, \quad \forall v,t \quad (10)$$

$$-Y_{l,c,t} + \sum_{u=1}^{C\cup L}\left(Z_{l,u,v,t} + Z_{u,c,v,t}\right) \le 1, \quad \forall l,c,v,t \quad (11)$$

$$\sum_{l=1}^{L} X_{k,l,p,t} \le CapK_{k,p} Z_k, \quad \forall k,p,t \quad (12)$$

$$V'_{l,p,t} + Q_{l,p,t} \le CapL_{l,p} Z_l, \quad \forall l,p,t \quad (13)$$

$$\sum_{p=1}^{P} X_{k,l,p,t} \le \sum_{p=1}^{P} Cap_v R_{k,l,v,t}, \quad \forall k,l,t \quad (14)$$

$$Tc_{l,c,v,t} \ge Ti_{l,c,v} - M.\left(1 - Z_{l,c,v,t}\right), \quad \forall l,c,v,t \quad (15)$$

$$Tc_{l,m,v,t} \ge Tc_{l,c,v,t} + Ti_{c,m,v} - M.\left(2 - Z_{c,m,v,t} - Y_{l,c,t}\right), \quad \forall l,c,m,v,t \quad (16)$$

$$Tc_{l,c,v,t} \le BH_c . Z_{l,c,v,t}, \quad \forall l,c,v,t \quad (17)$$

$$Tc_{l,c,v,t} \ge AH_c . Z_{l,c,v,t}, \quad \forall l,c,v,t \quad (18)$$

$$Tw_{l,v,t} \ge Tc_{l,c,v,t} + Ti_{c,l,v} Z_{c,l,v,t}, \quad \forall l,c,v,t \quad (19)$$

$$\sum_{k=1}^{K} R_{k,l,v,t} \le \sum_{c=1}^{C} Z_{l,c,v,t}, \quad \forall l,v,t \quad (20)$$

$$X_{k,l,p,t}, V'_{l,p,t}, Q_{l,p,t}, U_{c,v,t}, Tc_{l,c,v,t}, Tw_{l,v,t} \geq 0 \quad (21)$$

$$Z_k, Z_l, Z_v, Y_{l,c,t}, Z_{l,c,v,t}, R_{k,l,v,t} \in \{0,1\} \quad (22)$$

Equation (1) represents the first objective function value of the considered problem and minimize the total costs of location, routing, and inventory. Equation (2) minimizes GHG emissions between supply chain network levels. Equation (3) minimizes the maximum working hours of drivers in each time period. This relationship acts as an equilibrium relationship in the distribution of working hours between the drivers of each vehicle. Equation (4) shows the maximum transport capacity of the product available by the vehicle. Equation (5) shows the total flow of products (demand) in stock for transport to hospitals. Equation (6) ensures that each warehouse can only be allocated to one hospital. Equation (7) calculates the amount of inventory at the end of the period in the selected warehouse. Equation (8) is a constraint on sub-net removal. Equation (9) ensures that the vehicle can enter and leave each hospital only once.

Equations (10) and (11) ensure that the starting and ending points of the vehicle routing in the delivery of medical supplies to hospitals are the selected warehouse. Equations (12) and (13) show, respectively, the location of production and warehousing centers and ensure that their capacity for the production/distribution and storage of medical goods cannot be used until such centers are selected. Equation (14) shows the vehicle used to transport medical goods between production centers and warehouses. Equation (15) shows the time of arrival of the vehicle to the first hospital. Equation (16) shows the vehicle's arrival time to other hospitals based on the loading and unloading time and the traffic between nodes. Equations (17) and (18) ensure that the vehicle's arrival time to each hospital must be within a strict time frame. Equation (19) calculates the maximum working hours of the vehicle driver. Equation (20) shows the planned transport and ensures that the vehicle, upon entering the warehouse, is also responsible for distributing medical supplies to the hospitals. Equations (21) and (22) show the type of decision variables.

3. 5. Controlling the Uncertain Parameters with a Robust Fuzzy Method

Because of the dynamic and volatile nature of some important parameters (including transportation, operating, and demand costs) that are beyond planning, as well as the unavailability and even unavailability of historical data required at the design stage, these parameters are mainly based on expert opinions and experiences are estimated; Therefore, the above ambiguous parameters are formulated as indeterminate data in the form of triangular fuzzy numbers [47]. It is worth noting that it is difficult or sometimes impossible to assess the cost of transportation, operations, and definite demand for long-term decisions. Even if one can estimate a distribution function for these parameters, they may not behave similarly to previous data. Therefore, these parameters, which change in a long-term planning horizon, are considered as uncertain data. With this in mind, the robust fuzzy method is used to control the uncertain parameters of the considered problem.

$$\text{Min } \omega 1 = E[\omega 1] + \xi\left(E[\omega 1] - \omega 1_{(\min)}\right) + \eta \sum_{c=1}^{C} \sum_{p=1}^{P} \sum_{t=1}^{T} \sum_{l=1}^{L\cup C} \begin{pmatrix} Dem_{c,p,t}^{3} - Dem_{c,p,t}^{2} - \\ \alpha\left(Dem_{c,p,t}^{3} - Dem_{c,p,t}^{2}\right) \end{pmatrix} Z_{l,c,v,t} \quad (24)$$

$$E[\omega 1] = \sum_{k=1}^{K} H_k Z_k + \sum_{l=1}^{L} U_l Z_L + \sum_{v=1}^{V} F_v Z_v + \sum_{l=1}^{L\cup C} \sum_{c=1}^{L\cup C} \sum_{v=1}^{V} \sum_{t=1}^{T} \left(\frac{T_{l,c,v}^{1} + 2T_{l,c,v}^{2} + T_{l,c,v}^{3}}{4}\right) Z_{l,c,v,t} + \sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{v=1}^{V} \sum_{t=1}^{T} \left(\frac{T_{k,l,v}^{1} + 2T_{k,l,v}^{2} + T_{k,l,v}^{3}}{4}\right) R_{k,l,v,t} + \sum_{l=1}^{L} \sum_{p=1}^{P} \sum_{t=1}^{T} H_{l,p} Q_{l,p,t} + \sum_{l=1}^{L} \sum_{p=1}^{P} \sum_{t=1}^{T} \left(\frac{C_{l,p}^{1} + 2C_{l,p}^{2} + C_{l,p}^{3}}{4}\right) V'_{l,p,t} \quad (25)$$

$$\omega 1_{(\min)} = \sum_{k=1}^{K} H_k Z_k + \sum_{l=1}^{L} U_l Z_L + \sum_{v=1}^{V} F_v Z_v + \sum_{l=1}^{L\cup C} \sum_{c=1}^{L\cup C} \sum_{v=1}^{V} \sum_{t=1}^{T} T_{l,c,v}^{1} Z_{l,c,v,t} + \sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{v=1}^{V} \sum_{t=1}^{T} T_{k,l,v}^{1} R_{k,l,v,t} + \sum_{l=1}^{L} \sum_{p=1}^{P} \sum_{t=1}^{T} H_{l,p} Q_{l,p,t} + \sum_{l=1}^{L} \sum_{p=1}^{P} \sum_{t=1}^{T} C_{l,p}^{1} V'_{l,p,t} \quad (26)$$

$$\sum_{c=1}^{C} \sum_{l=1}^{C\cup L} \sum_{p=1}^{P} \left(\alpha Dem_{c,p,t}^{3} + (1-\alpha) Dem_{c,p,t}^{2}\right) Z_{l,c,v,t} \leq Cap_v Z_v, \quad \forall v,t \quad (27)$$

$$V'_{l,p,t} = \sum_{c=1}^{C} \sum_{v=1}^{V} \begin{pmatrix} \alpha Dem_{c,p,t}^{3} + \\ (1-\alpha) Dem_{c,p,t}^{2} \end{pmatrix} Z_{l,c,v,t}, \quad \forall l,p,t \quad (28)$$

Equations (2), (3), (6) – (23) (29)

In Equation (24), the first term refers to the expected value of the first objective function using the mean values of the uncertain parameters of the model. The second term refers to the cost of the penalty for deviating from the expected value of the first objective function (optimality stability). The third term also shows the total cost of the demand deviation penalty (uncertain parameter). Therefore, parameter ξ is the weight coefficient of the objective function, and η is the penalty for not estimating the demand. The parameter α, as the rate of uncertainty, indicates the value of the levels of fuzzy numbers, which must be a number between 0.1 and 0.9.

4. NEUTROSOPHIC FUZZY PROGRAMMING METHOD

Since the model is considered a multi-objective problem, the neutrosophic fuzzy method is thus proposed to solve the problem in this paper. Multi-objective decision models are the most common type of mathematical model that have conflicting goals. In such cases, the aim is to achieve the optimal value of all conflicting objective functions simultaneously. In such problems, the decision-maker expresses the importance of his/her preferences by providing an optimal weight $\beta \in [0,1]$ to each objective function. With a high value of β weight in an objective function value, the decision-maker's preference in that function is higher. Zimmermann [48] maximized decision-making preferences in simultaneously achieving objective function values by introducing a multi-objective fuzzy programming method. Developing a multi-objective fuzzy programming method called intuitive fuzzy programming could solve various mathematical problems in the following years. In these programming methods, flexibility in element membership functions was also possible.

This method has been studied in various real-life issues and problems extensively. In recent years, it has been observed that living conditions may have neutral thoughts about an element in the set. Neutral or uncertain ideas about the elements fall between a degree of falsehood and truth. Thus, by developing the intuitive fuzzy programming method, Smarandache [49] examined the neutrosophic fuzzy programming method, which has three sets of memberships: truth (i.e., degree of belonging), uncertainty (i.e., degree of belonging to some extent), and falsehood (i.e., degree of non-belonging). According to the neutrosophic fuzzy programming method developed in this paper, the sustainable biomass supply chain network model with four conflicting objective functions is solved. Hence, each objective function has three terms: truth membership, non-determination, and falsehood. Therefore, the neutrosophic fuzzy programming method is important in optimizing multi-objective problems by considering neutral thoughts.

Consider a multi-objective model, where D represents a set of fuzzy decisions, G is a set of fuzzy objective functions, and C represents fuzzy constraints. Therefore, the set of fuzzy decisions is represented as $D = G \cap C$. The set of fuzzy neutrosophic decisions (D_n) along with the set of neutrosophic fuzzy target functions (G_o) and the set of neutrosophic fuzzy constraints (C_m) are expressed as follows:

$$D_n = (\cap_{o=1}^{O} G_o)(\cap_{m=1}^{M} C_m) = (w, P_D(w), Q_D(w), R_D(w)) \tag{30}$$

s. t.

$$P_D(w) = \begin{Bmatrix} min\ PG_o(w), & \forall o \in O \\ s.t. & \\ PC_m(w), & \forall m \in M \end{Bmatrix}$$

$$Q_D(w) = \begin{Bmatrix} max\ QG_o(w), & \forall o \in O \\ s.t. & \\ QC_m(w), & \forall m \in M \end{Bmatrix}$$

$$R_D(w) = \begin{Bmatrix} max\ RG_o(w), & \forall o \in O \\ s.t. & \\ RC_m(w), & \forall m \in M \end{Bmatrix}$$

where $P_D(w)$ is a truth membership function, $R_D(w)$ is a non-deterministic membership function, and $R_D(w)$ is a false membership function under neutrosophic fuzzy decisions D_n. Each of the above membership functions has a top and bottom boundary, which is obtained as the following relation for all membership functions:

$$U_o = max(Z_o(X)) \qquad L_o = min(Z_o(X)) \tag{31}$$

Therefore, the upper and lower bounds of the neutrosophic fuzzy membership function can be calculated for truth, non-determination, and falsehood, respectively, as follows.

$$\begin{aligned} &U_o^P = U_o, \quad L_o^P = L_o \\ &U_o^Q = L_o^P + a_o, \quad L_o^Q = L_o \\ &U_o^R = U_o^P, \quad L_o^R = L_o^P + b_o \end{aligned} \tag{32}$$

In the above relation a_o and b_o is a predefined value between 0 and 1. Given the above, the linear membership function for a neutrosophic fuzzy framework is as follows.

$$D_n = (\cap_{o=1}^{O} G_o)(\cap_{m=1}^{M} C_m) = (w, P_D(w), Q_D(w), R_D(w)) \tag{33}$$

$s.t.$:

$$P_o(Z_o(X)) = \begin{Bmatrix} 1 & if \quad Z_o(X) < L_o^P \\ \frac{U_o^P - Z_o(X)}{U_o^P - L_o^P} & if \quad L_o^P \le Z_o(X) \le U_o^P \\ 0 & if \quad Z_o(X) > U_o^P \end{Bmatrix}$$

$$Q_o(Z_o(X)) = \begin{Bmatrix} 1 & if \quad Z_o(X) < L_o^Q \\ \frac{U_o^Q - Z_o(X)}{U_o^Q - L_o^Q} & if \quad L_o^Q \le Z_o(X) \le U_o^Q \\ 0 & if \quad Z_o(X) > U_o^Q \end{Bmatrix}$$

$$R_o(Z_o(X)) = \begin{Bmatrix} 1 & if \quad Z_o(X) > U_o^R \\ \frac{Z_o(X) - L_o^R}{U_o^R - L_o^R} & if \quad L_o^R \le Z_o(X) \le U_o^R \\ 0 & if \quad Z_o(X) < L_o^R \end{Bmatrix}$$

Therefore, the controlled model of the multi-depot VRP under COVID-19 pandemic conditions by a neutrosophic fuzzy programming method based on the above equations is as follows:

$$\max \sum_{o=1}(\mu_o + \vartheta_o - \delta_o)$$

s.t.

$$P_o(Z_o(X)) \geq \mu_o, \quad \forall o$$
$$Q_o(Z_o(X)) \geq \vartheta_o, \quad \forall o$$
$$R_o(Z_o(X)) \leq \delta_o, \quad \forall o$$
$$\mu_o \geq \vartheta_o, \quad \forall o \tag{34}$$
$$\mu_o \geq \delta_o, \quad \forall o$$
$$0 \leq \delta_o + \mu_o + \vartheta_o \leq 3, \quad \forall o$$
$$\delta_o, \mu_o, \vartheta_o \in (0,1)$$
$$Equations\ (24-29)$$

5. PROBLEM ANALYSIS

5. 1. Solving the Small-sized Problem In this section, considering the three objective functions of the mathematical model, a numerical example is designed to analyze and solve the small-sized problem by a neutrosophic fuzzy programming method. This test problem consists of 3 production centers, 3 warehouses, 4 hospitals, 2 types of medical goods, 5 types of vehicles, 2 periods, and random data based on uniform distribution function as described in Table 1. Using random data based on the uniform distribution function is the lack of access to real-world data.

Table 2 shows the membership functions for the neutrosophic fuzzy method for truth, non-determination, and falsehood, respectively. Using Equation (34), the efficient solution obtained using the membership functions obtained is also shown in this table.

According to the obtained efficient solution, it is observed that the total cost, the amount of GHG emission, and the maximum working hours of drivers are 45305, 252, and 46, respectively. Therefore, Figure 2 shows the output variables of the problem based on the solution obtained from the neutrosophic fuzzy programming method. Based on the results of this figure, it can be stated that when the three objective functions are optimized simultaneously, the number of warehouses constructed and the type and routing of vehicles will change. Therefore, it can be seen that two warehouses are used to distribute medical goods to hospitals. On the other hand, it can be said that the vehicle is routed with minimal driver density, and this leads to a possible reduction in the prevalence of the COVID-19 virus.

TABLE 1. Values of the problem parameters based on the uniform distribution function

Parameter	Approximate interval	Parameter	Approximate interval
H_k, U_l	$\sim U[10000{,}12000]$	$CapK_{k,p}$	$\sim U[25{,}60]$
F_v	$\sim U[1000{,}2000]$	$CapL_{l,p}$	$\sim U[25{,}60]$
$Co2_{k,l,v}$	$\sim U[30{,}40]$	Cap_v	$\sim U[150{,}160]$
$Ti_{l,c,v}$	$\sim U[10{,}30]$	AH_c	$\sim U[5{,}10]$
$H_{l,p}$	$\sim U[3{,}5]$	BH_c	$\sim U[150{,}300]$
Parameter	**Optimistic**	**Possible**	**Pessimistic**
$Dem_{c,p,t}$	$\sim U[20{,}25]$	$\sim U[25{,}30]$	$\sim U[30{,}35]$
$T_{k,l,v}, T_{l,c,v}$	$\sim U[10{,}15]$	$\sim U[15{,}20]$	$\sim U[20{,}25]$
$C_{l,p}$	$\sim U[1{,}2]$	$\sim U[2{,}3]$	$\sim U[3{,}4]$

TABLE 2. Membership functions obtained from the neutrosophic fuzzy method

	$\omega 1$	$\omega 2$	$\omega 3$
Upper bound	75148	281	48
Lower bound	34703	234	36
U_o^P	75148	281	48
U_o^Q	75182	293	50
U_o^R	75148	281	48
L_o^P	34703	234	36
L_o^Q	34703	234	36
L_o^R	34810	240	38
Solution	45305	252	46

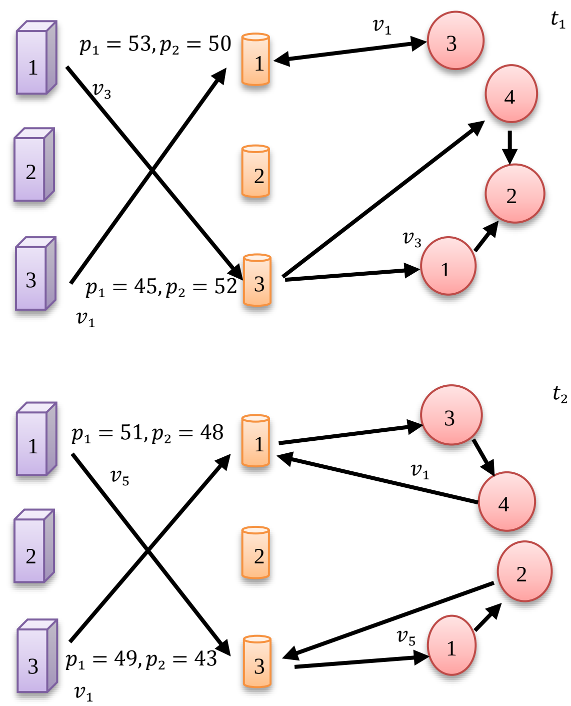

Figure 2. Routing of a multi-warehouse vehicle based on the neutrosophic fuzzy method

5. 2. Sensitivity Analysis In this section, the effect of the behavior of output variables due to changes in the main parameters of the model is investigated. Therefore, first, the effect of the behavior of the values of the objective functions in exchange for changes in the uncertainty rate is investigated. Considering the efficient solution of the problem with the neutrosophic fuzzy method at an uncertainty rate of 0.5, Table 3 shows the values of the objective functions of the problem at different rates of uncertainty.

According to the results of Table 3, it can be stated that by increasing the uncertainty rate, due to the increase in production and distribution volume and limited capacity of vehicles, more equipment should be used to distribute and transfer medical goods from the production center to the warehouse. Accordingly, the costs of the entire network increase. While increasing the number of vehicles and the proper distribution of goods between vehicles, the drivers' maximum working hours decrease, and the amount of GHG emissions increases. Also, by examining the effect of the uncertainty rate, it can be concluded that by increasing the uncertainty rate, due to an increase in the number of vehicles and the number of people involved in the distribution of medical goods, the probability of increasing the prevalence of COVID-19 increases. Figure 4 shows the trend of changes in the objective function values of the problem in exchange for changes in the rate of uncertainty.

In the following and another analysis, changes in the objective function values in exchange for changes in the time window of delivery of medical goods to the hospital are examined. Since the intended time window is of the hard type, vehicles must meet the hospital's request within the stipulated time and have no right to exceed that time. Table 4 shows the changes in the objective function values of the problem in exchange for changes in the upper bound of the time window. According to the results of this table, it is observed that by reducing the upper limit of the time window, due to the limited delivery time of hospital demand, vehicles have to travel shorter routes. Therefore, the need to use more vehicles is evident. Therefore, by reducing the upper limit of the time window, the total costs and the amount of greenhouse gas emissions increase, and the maximum working hours of drivers decrease.

Figure 5 shows the changes in the objective function values of the considered problem in exchange for changes in the upper bound of the time window. Based

TABLE 3. Trend of changing the objective function values of the problem in exchange for changes in the uncertainty rate

α	$\omega 1$	$\omega 2$	$\omega 3$
0.1	42523	229	52
0.2	43125	236	50
0.3	44268	240	50
0.4	44923	248	48
0.5	45305	252	46
0.6	45823	258	46
0.7	45936	263	45
0.8	46290	271	42
0.9	46730	283	42

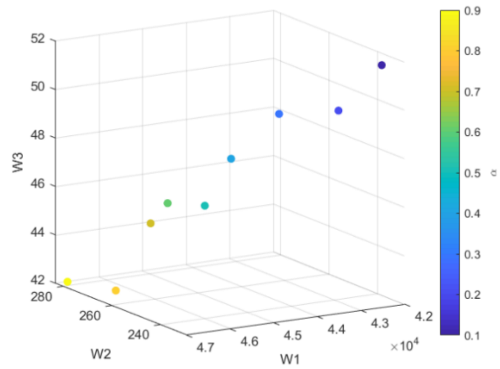

Figure 4. Trend of changing the objective function values of the problem in exchange for changes in the amount of the uncertainty rate

TABLE 4. Process of changing the objective function values of the problem in exchange for changes in demand

BH_c	$\omega 1$	$\omega 2$	$\omega 3$
-30%	47110	263	42
-20%	46250	260	42
-10%	45930	258	44
0	45305	252	46
+10%	44830	243	47
+20%	44730	240	49
+30%	43250	237	50

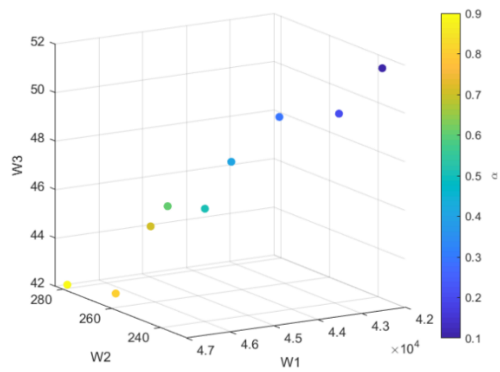

Figure 5. Process of changing the first and second objective function values in exchange for changes in the upper limit of the time window

on the results of this figure, it can be stated that with the shortening of the time window, the timing of the distribution of medical goods to the hospital has become more complex. As a result, more vehicles should be used to distribute medical goods. This is a waste of more drivers. As a result, the prevalence of the COVID-19 virus is likely to increase.

Table 5 shows the changes in the values of the objective functions in exchange for changes in vehicle capacity.

In the most important sensitivity analysis of the problem on the capacity of the vehicle, it was determined that by increasing the capacity of the vehicle, fewer vehicles are used, and as a result, the cost and amount of greenhouse gas emissions are reduced. On the other hand, this has led to a decrease in the prevalence of the COVID-19 virus. Figure 6 shows the changes in the objective function values of the considered problem in exchange for changes in the vehicle capacity.

TABLE 5. Process of changing the objective function values of the problem in exchange for changes in vehicle capacity

Cap_v	$\omega 1$	$\omega 2$	$\omega 3$
-30%	46123	269	43
-20%	45973	262	44
-10%	45845	257	46
0	45305	252	46
+10%	45126	249	47
+20%	44975	245	47
+30%	44235	240	49

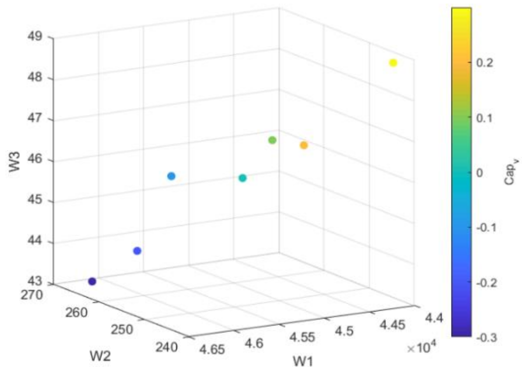

Figure 6. Trend of changing the objective function values of the problem in exchange for changes in the vehicle capacity

6. CONCLUSION

Due to the importance of vehicle routing and inventory management in this research, a multi-warehouse vehicle routing model under the COVID-19 pandemic conditions has been presented. The importance of locating warehouses and distribution centers in logistics systems was not less than vehicle routing and covered most system costs. In the model presented in this paper, three levels (i.e., production centers, warehouses, and hospitals as the first, second, and final levels, respectively) were considered. Therefore, the location of facilities in production centers, warehouses, and routing-inventory was at the level between warehouses and the customer. The prevalence of the COVID-19 virus and the need for careful planning for the transfer of hospital equipment led to the design of an uncertain model of vehicle navigation in this paper. They then controlled the model using a robust fuzzy method.

To optimize the multi-objective model (i.e., minimizing the total cost, minimizing the amount of GHG emissions, and minimizing the maximum working hours of drivers) led to the use of the neutrophilic fuzzy programming method. The model implementation results showed that reducing the number of vehicles decreased the amount of GHG emissions and the prevalence of the COVID-19 virus. In contrast, the drivers' working hours increased and were unbalanced. Also, by examining the amount of the uncertainty rate, it was observed that by increasing this parameter due to the increase in production, distribution volume, and limited capacity of vehicles, more equipment should be used for distribution and transfer of medical goods from the production center to the warehouse. Accordingly, the costs of the entire network increased. While increasing the number of vehicles and the proper distribution of the volume of goods between vehicles, the maximum working hours of drivers decreased, and the amount of GHG emissions increased. In the most important sensitivity analysis of the problem on the capacity of the vehicle, it was determined that by increasing the capacity of the vehicle, fewer vehicles are used. As a result, the cost and amount of greenhouse gas emissions are reduced. On the other hand, this has led to a decrease in the prevalence of the COVID-19 virus. At the end, according to the analysis, the greatest impact on the spread of the COVID-19 virus is related to the uncertainty rate. Therefore, with the increase of uncertainty rate, due to the increase in demand and increase in vehicle traffic, the probability of spreading the COVID-19 virus increases. According to the presented mathematical model in this paper, it is suggested that this model be solved using meta-heuristic algorithms and implemented in a real-case study to develop and apply it. It is also recommended that, due to the market's competitive nature, competition between two similar supply chain networks be considered.

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Persian Abstract

چکیده

شیوع ویروس COVID-19 در سراسر جهان و ایجاد مشکلات جدی در توزیع تجهیزات پزشکی، منجر به آن شده است تا در این مقاله به مدل‌سازی مسئله مسیریابی وسیله نقلیه چند انباره تحت عدم قطعیت در شرایط پاندمی COVID-19 پرداخته شود. هدف اصلی مدل ارائه‌شده مکان‌یابی انبارها و مراکز تولید و مسیریابی وسایل نقلیه جهت توزیع کالاهای پزشکی به بیمارستان‌ها می‌باشد. برای کنترل پارامترهای غیرقطعی مسئله نظیر تقاضا، هزینه‌های انتقال و توزیع از روش استوار فازی استفاده شده است. نتایج تاثیر عدم قطعیت با به کارگیری روش برنامه‌ریزی فازی نوتروسوفیک نشان می‌دهد، با افزایش مقدار تقاضا، حجم تبادلات کالاهای پزشکی افزایش یافته و تعداد وسایل نقلیه مورد استفاده جهت توزیع کالاها نیز افزایش یافته است. این امر منجربه افزایش هزینه‌های کل مسئله و میزان انتشار گازهای گلخانه‌ای شده است. همچنین بررسی نتایج نشان می‌دهد استفاده از وسایل نقلیه بیشتر منجربه کاهش خستگی کارکنان به جهت توزیع کالاهای پزشکی و کاهش شیوع ویروس COVID-19 می‌شود. در مهمترین تجزیه و تحلیل حساسیت مشکل بر روی ظرفیت وسیله نقلیه، مشخص شد که با افزایش ظرفیت خودرو، از وسایل نقلیه کمتری استفاده می‌شود و در نتیجه هزینه و میزان انتشار گازهای گلخانه‌ای کاهش می‌یابد. از سوی دیگر، این امر منجر به کاهش شیوع ویروس COVID-19 شده است.