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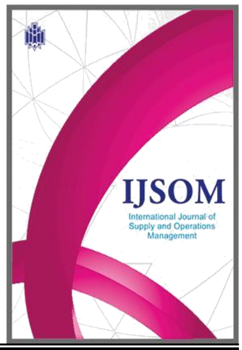

A Robust Possibilistic Programming Model for Disaster Relief Routing under Information and Communication Technology

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Abstract
In this paper, we investigate an integrated procurement and capacitated vehicle routing problem for the distribution of multiple relief goods after the disaster, to determine the best tour for vehicles as well as the best selection of multiple relief goods and their quantity to be loaded on vehicles. Due to the uncertain nature of the parameters, the demand distribution and cost parameters are considered as fuzzy parameters. Furthermore, this paper examines the impact of information and communication technology in the affected areas so that instant information, communicate between the affected areas and the disaster coordination center due to new events caused by the disaster. We have examined the impact of information and communication technology on reducing demand uncertainty such that with consideration of the cost of equipping GPS in affected areas, as well as its impact on reducing demand uncertainty and the cost of dissatisfaction as a result; the best affected areas are selected to be equipped with GPS. To have robust solutions, a robust possibilistic programming model is proposed. The results of the model are shown in a real case study in district 7 of Tehran which acclaim that the proposed model achieves a better result than the traditional models without considering ICT.

Keywords: Disaster; Relief; Vehicle Routing Problem; Information and Communication Technology; Robust Possibilistic Programming; Uncertainty.

1. **Introduction**

Over the past 70 years, natural disasters have grown exponentially in numbers and sizes (Ozdamar and Ertem, 2015). Many types of unpredictable disasters, including terrorist attacks, wars, earthquakes, economic crises, devaluation of currencies in Asia, SARS, tsunamis, strikes, computer virus attacks, etc. have been occurred (Tang, 2006). One of the important fields seeking to reduce the negative consequences of a natural disaster is humanitarian logistics (Mohamadi et al., 2017). In general, the humanitarian relief chain rapidly provides the provision of supplies for affected people to alleviate human suffering, through efficient and effective resource allocation (Tofighi et al., 2016). disaster management is a discipline that involves preparing for disaster before it happens, responding to disasters immediately, as well as rebuilding societies after natural or human-made disasters happen (Safaei et al., 2018). The distribution of emergency supplies and relief goods is essential for successful operations in natural disasters after the occurrence, which is the final stage of a humanitarian relief chain. Fast and efficient distribution systems can minimize the number of casualties and take immediate relief to the beneficiaries affected by disasters. In the early times of a disaster, most of the parameters of the humanitarian logistics system (e.g., demand of affected area (AA), transportation, and unsatisfactory costs and capacities) are tainted by the high degree of uncertainty in a real-life situation because of imprecise nature of disaster logistics. Therefore, neglecting the uncertainty in the management of a disaster supply chain may impose high damages to lives (Pishvaee et al., 2012).

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According to Pishvaee and Torabi (2010), uncertainty can be assumed as (1) flexibility in objectives or constraints and/or (2) uncertainty in data. Flexibility (fuzziness) refers to the flexible target value of constraints or goals which is modeled by fuzzy logic. Flexible mathematical programming models are used to handle this kind of uncertainty. The uncertainty in data can be categorized into two groups: (1) randomness in parameters which are usually modeled via stochastic programming approaches and (2) epistemic uncertainty that deals with lack of knowledge about parameters value. Possibilistic programming approaches are used to cope with this kind of uncertainty.

When the disaster occurs, the important parameters of the problem adopt unclear and imprecise values which is a usual phenomenon, because of the disaster feature and lack of certain knowledge that causes the values of these parameters to be influenced by subjective factors. This vagueness, as a result, makes these parameters follow fuzzy logic, which is called epistemic uncertainty. One of these parameters is the relief demand, which is always the most critical factor in humanitarian disaster management in the early hours of a disaster, and the degree of success and satisfaction of vehicle routing issues in delivering disaster relief items depends on maximum satisfaction of it in the arranged time. Hence, in the recent literature on earthquake disaster management, the demand for relief items has been studied as an uncertain parameter.

Recently, uncertainty on demand rate, in disaster relief vehicle routing problems for transportation of relief goods, has been considered in the literature of disaster management. The vehicle routing problem (VRP), first proposed by Dantzig and Ramser (1959), has been recognized as an essential problem in the fields of transportation and logistics (Yu and Yang, 2019). This would become more practical while the vehicle routing problem is integrated with procurement decisions for relief goods in disaster relief models. In other words, decisions consist of routing and distribution along with the determination of the optimal choice of relief items to be loaded in vehicles and the quantity of them due to their weight and utility, can be scheduled as integrated decisions to be taken simultaneously in the model which is neglected in the literature of disaster routing studies.

Due to the status of the AAs during the disaster, such as the urgent need for relief items, the presence of aftershocks and the increase in the number of damages and demand of relief items, etc.; Accurate estimates of the extent of damage or determining AAs and the demand for relief items are difficult and in some cases impossible. Therefore, the dynamics of the problem information, such as the AAs and their demand for relief items, is a reasonable and important assumption and corresponds to the reality of the problem. As a result, AAs information on this issue is dynamic and changes during relief operations. The practical infrastructure to develop the communication system between the AAs and the disaster coordination center (DCC) in times of disaster is setting an information and communication technology (ICT) in terms of global positioning system (GPS) connection to deal with the dynamism of the problem.

The use of ICT requires the creation of GPS on rescue vehicles as well as AAs so that the necessary information such as loading relief items from the depot, their delivery to the affected areas, as well as information including changes in the demand, are communicated online between the DCC and the AAs through vehicles. The presence of ICT in disaster relief problems can have a significant impact on demand and relief management by reducing demand uncertainty, reducing delays in information delivery and thus relief time, and so on. However, ICT has been neglected in humanitarian logistics studies.

In VRP studies, the transportation network might be unable to satisfy all the demands because of capacity constraints or other limitations (Rabbani et al., 2021).

In this paper, we study an integrated procurement and vehicle routing problem to distribute post-disaster relief items due to achieving the best selection of relief items and their quantities to load on vehicles as well as the best tour for relief vehicles to reduce costs. Demand for relief items and cost parameters are associated with epistemic uncertainty. We have complemented our effort on the uncertainty context, by incorporating robust possibilistic programming. In addition, the use of GPS between the AAs and the DCC through vehicles is applied in this study. Since it is assumed that the existence of ICT affects the model by reducing demand uncertainty, this model determines the best AAs to be equipped with GPS by balancing the costs of GPS establishment and the costs of unsatisfactory demand that increases due to uncertainty intensification.

Due to the geographical location of Iran between two Eurasian and Arabian plates, which leads to being a seismic-prone area (Ghasemi et al., 2020), we apply this approach based on real data in a real case of the 7th district of Tehran. The results show the superiority of the proposed model over the traditional model without applying ICT.

The rest of the paper is organized as follows. In Section 2, the relevant literature is reviewed. The general problem description of the problem, as well as the effect of using ICT on reducing demand uncertainty, is illustrated in Section 3. Section 4 describes the assumptions, the mathematical model, and the constraints of the problem. In Sections 5, the possibilistic programming model and the robust possibilistic programming model are presented, respectively. Section 6 describes the case study, related information and the results of the proposed model on the case study as well as the validation of the model and sensitivity analysis on parameters. Finally, Section 7 provides conclusions and suggestions for future research.

2. Literature Review

The improvement of transport operations has been traditionally achieved with the use of mathematical modeling, operations research, and simulation methods (Villarreal et al., 2016). One of the main operational decisions related to the distribution of emergency goods that have been proposed to increase the efficiency of transportation systems is the routing of vehicles. The purpose of a vehicle routing problem is to find a set of routes for multiple vehicles from one or more depots to several customers and return to the depots without violating the capacity of any vehicle. This is about to work with mathematical models and optimization so that the distance traveled, the total travel time, the number of transport vehicles, delayed finds, and cost functions are minimized, and eventually, customer satisfaction is maximized. The routing issues are an integral part of operational decisions.

Haghani and Oh (1996) conducted the first attempt on vehicle routing and transportation of relief goods. In these models, vehicle routing for the distribution of relief items in relief and rescue operations has been investigated after the disaster. These authors proposed deterministic models for the network flow problem as linear programming with time window limitations which are solved by an innovative algorithm, and the objective function in these models has been considered to minimize the total cost.

There are many studies in the literature of vehicle routing, which studied deterministic models in the disaster field. Ozdamar et al. (2004) improved the model conducted by Haghani and Oh (1996) by introducing a time lag in equations and variables. They investigated logistical planning for the delivery of goods to distribution centers in the affected areas. The network has been investigated in this research, as a time-dependent dynamic transportation problem and it is repeated iteratively for the delivery of aids. Yi and Ozdamar (2007) presented a mathematical model for emergency evacuation in the response phase in which vehicle routing problem is addressed by the limitation of capacity and transferring the injuries to medical centers as well as the distribution of relief supplies. Lin et al. (2011) proposed a multi-period multi-commodity logistics model for routing and planning the critical commodity distribution in the disaster response phase with a deterministic demand rate. The model aims to minimize the total unsatisfied demand and total travel time. In the study, incorporated by Ozdamar and Demir (2012), with an extension of the model described by Yi and Ozdamar (2007), both of the injuries evacuation and relief items distribution, and even routing decisions with a hierarchical clustering are investigated concerning deterministic demand. Huang et al. (2012) investigated the routing and allocation of supply resources models in helping those affected by disasters. They presented three key factors in routing and resource allocation in disasters such as efficiency, usefulness, and equal benefit. To examine these three criteria, they considered the same mathematical model with a different objective function. They provide efficiency, to minimize routing costs and supply resources, and defined usefulness, to minimize the delivery time to the affected individuals, and equal benefit, as the minimum demand satisfaction differences. Afshar and Haghani (2012) studied the integrated supply chain operations performed in response to extreme natural disasters. They noticed that the most important objective of their research is satisfying the maximum level of demand. The study was based on the assumption of temporary relief centers, where the fleet should gather the supplies from the depots located outside the disaster zone. Rath and Gutjahr (2014) proposed a deterministic optimization model with three objectives such as humanitarian, short-term, and medium-term economic objective functions. The routing decision is proposed to help disaster areas through a fleet of transportation with identical capacities. Relief commodities are transferred from a series of plants to the warehouses and then to the demanded areas. Consequently, the model is solved by the ε-constraint method and innovative algorithm of variable neighborhood search (VNS).

Davoodi and Goli (2019) developed an integrated location routing model for relief distribution to minimize the late arrival of relief vehicles in critical situations. To increase the operational speed of the disaster logistics system, vehicle routing is underlain by the covering tour approach. A hybrid benders decomposition and variable neighborhood search are presented to solve the model.

In addition, there are some recent and new researches that have taken into account the rate of demand as deterministic to simplify their modelings such as Altheeb et al. (2017) who addressed three approaches of the evacuation of injuries from disaster areas to medical centers, transportation of workforce from distribution centers to disaster areas and the operation of last-mile distribution concerning vehicle routing problem decisions. Moreover, Tavana et al. (2018) Investigated and multi-level humanitarian logistics network considering locating Central warehouses, inventory management of perishable goods in the pre-disaster phase, and the routing of relief vehicles in the post-disaster phase with deterministic demand. This study aims to minimize the cost and time in relief operations. In this study the best location for local warehouses from the designated locations, the capacity of the central warehouses, and the best order policy for storing perishable goods are determined. Other deterministic efforts on disaster relief routing can be introduced such as (Ekici and Ozener, 2020; Çankaya et al., 2019; Wei et al., 2020; Sakiani et al., 2020).

One of the most important factors in the development of transportation is the impact of information uncertainty. Due to the expanding competition in the field of transportation and the demand of customers to receive services faster at the desired time and on the other hand increasing the factors generating uncertainties such as traffic, road accidents, and so on, ignoring uncertainties may lead to enormous costs in transportation. The impact of uncertainty on input information such as demand has a significant impact on the optimization of the approach used. Balcik et al. (2008) extended the deterministic model proposed by Haghani and Oh (1996), by including uncertainties that exist in estimating route capacities and demand/supply of first-aid commodities. They presented a model with a time horizon to obtain intrinsic uncertainty in supply and demand. They associated travel expenses on arcs with the type of vehicles to demonstrate the compatibility between the vehicle and road. Using this approach, if a road is damaged or out of usage by a particular vehicle, the travel cost along that arc is considered a very large number.

There are some efforts in the literature that have addressed demand uncertainty rely on a dynamic context where the information is updated over time. Maghfiroh and Hanoka (2018) have addressed the application of dynamic routing problems to transport relief goods to disaster areas during the disaster. Capacitated and heterogeneous vehicles, multiple paths, destinations with different accessibilities, stochastic demand, and prediction of new locations, are used in the problem assumptions. A simulated annealing algorithm is used to manage the dynamic properties of the problem. The main proposal for modeling this problem is to find a good combination of heterogeneous vehicles to minimize response time. To manage uncertainty and unpredictability, this paper presents a vehicle routing model with random and dynamic demand and the use of vehicles to minimize relief time with consideration of slacks and shortages.

Recently, Alinaghian et al. (2019) presented a new mathematical model for locating temporary relief centers and the dynamic routing of air rescue vehicles to transport relief items to the affected areas during a disaster. In the proposed model, finding temporary relief centers in the affected areas, the allocation of damaged points to these centers, and the routing of relief vehicles under dynamic conditions are considered to be minimized. Furthermore, since the disaster is due to uncertain conditions such as unclear demand, lack of accurate information, the occurrence of aftershocks, and the breakdown of roads are the dynamic information, they would change during the time horizon.

There are several uncertainty approaches in the literature of disaster vehicle routing and distribution of relief items. Several articles used uncertainties in demand and supply literature. Some of the studies involved in dealing with humanitarian logistic management have taken into account two-stage stochastic uncertainties on parameters such as demand, supply, service time, and so on. For instance, Ahmadi et al. (2015) presented a location routing problem with multiple uses of vehicles and standard relief time for last-mile distribution after an earthquake. In their effort, a two-stage stochastic programming model is developed with the assumption of network failure, random travel time, and deterministic demand rate; using a case study in the San Francisco district. Mete and Zabinsky (2010) described a two-stage stochastic model which deals with the location problem of depots in the first stage, and the transportation of relief goods in the second stage. They assumed demand as a random parameter and adopted the second modeling approach in the second stage to solve a scenario with a 21-node relief network and 14 vehicles. Sabouhi et al. (2020) investigated two-stage stochastic programming for the distribution of relief items with demand uncertainty. In this study, vehicles and distribution centers have limitations in capacity. The objective of this study is to minimize service time with the assumption of disruptions on roads. Zhong et al. (2020) addressed a two-stage stochastic model for decisions of vehicle routing and facility location with consideration of both the reliability and unreliability aspects of demand variability in disaster relief. The proposed model includes conditional value at risk with regret (CVaR-R) which is defined as the expected regret of worst-case scenarios as a risk measure. In another study conducted by Rennemo et al. (2014), a three-stage mixed-integer stochastic programming model was presented for post-disaster relief distribution. The first stage deals with the construction of local distribution centers and the number of goods that must be transported from each of the main distribution centers. The second stage deals with vehicle routing decisions where the number of vehicles in each local distribution center and the amount of demand at each of the affected areas are determined. The demand uncertainty as a scenario-based stochastic element in the studied network is examined in the third stage.

Some researchers attended to more complex uncertainties such as robustness which adapt with extreme uncertainties in comparison to the previous uncertainty approaches. In the research Vahdani et al. (2018) proposed, each of the three issues, location, inventory, and routing problems have been investigated under uncertain conditions using the robust optimization approach presented by Ben-Tal et al. (2009). In this study, two multi-objective, multi-period models in a triple-level supply chain with time window limitation are determined. The goods are categorized into two vital and non-critical categories. In the first stage of these models, strategic decisions are taken for finding distribution centers and warehouses with different capacities as well as decisions related to storing goods in warehouses and distribution centers. In this stage, the minimization of costs of the distribution centers and warehouses and costs of maintenance and shortage of goods is the objective of the problem. In the second stage, operational decisions for vehicle routing as well as the distribution of relief goods to the disaster areas are considered as time window constraints. The objective of this stage is to minimize the cost of transportation and time and maximize the reliability of service routes. Li & Chung (2019) afforded another research that employed uncertainty generated by Ben-Tal et al. (2009), in demand and travel time to distribute relief goods after the disaster. They presented a capacitated vehicle routing problem with split delivery. Najafi et al. (2013) is another attempt that used the robust optimization approach presented by Ben-Tal et al. (2009) in the field of disaster relief routing. Besides, there are some researches associated with scenario-based robust optimization such as Bozorgi-Amiri et al. (2013), Safaei et al. (2018), and Haghi et al. (2017).

Possibilistic programming is another uncertainty approach in dealing with subjective data. Few researchers addressed possibilistic programming in the field of vehicle routing and disaster relief distribution. Goli & Malmir (2020) proposed a covering tour approach in a routing allocation model to reduce the response time of relief items distribution after a disaster considering demand as an uncertain parameter with the fuzzy distribution. A fuzzy programming and robust optimization based on the robust approach of Ben-Tal et al. (2009) is recently applied by Mohammadi et al. (2020) to minimize the relief operations time, total logistics costs and the variation between upper and lower bounds of transportation cost of distribution centers to regulate the workload of them. The research includes multiple decisions such as location, routing, allocation and fair distribution of relief items. Mamashli et al. (2021) investigated a routing-allocation problem in the response phase of disaster management to minimize total traveling time, total environmental impacts and total demand loss. A fuzzy robust stochastic optimization approach is utilized to cope with uncertain data arisen in disaster conditions. Moreover, Vahdani et al. (2021) applied a bi-objective optimization model to plan a humanitarian districted logistics network, in which the decisions concerning emergency facility location-allocation, redistricting, service sharing, and routing of vehicles are considered simultaneously. Two types of vehicle routing problems, namely closed and open, are worked out for land and air routing, respectively. Also, a hybrid robust optimization is proposed to handle the nature of uncertainty in demand and supply. Nodoust et al. (2021) proposed a location-routing problem for the distribution of relief goods after disaster. They investigated demand as a random fuzzy variable and developed a robust possibilistic programming approach. The hybrid uncertainty applied in this research is a scenario-based possibilistic-stochastic programming for demand parameter.

It can be concluded from the literature review of disaster routing problems that most of the researchers coped with deterministic demand or mainly two-stage stochastic programming. Yet, the robust possibilistic programming approach is not applied extensively in disaster routing studies. There is also no attempt to investigate integrated procurement and routing problem in the literature of the proposed paper. On the other hand, using ICT due to having an online connection to reduce the intensity of uncertainty, has been neglected in the relevant literature.

In this paper, an integrated procurement and vehicle routing problem is developed to determine the best selection of relief items and their quantity to be loaded on relief vehicles; and the best tour of vehicles to distribute relief items among AAs. This integration is managed by balancing the utility of each type of goods and the volume they occupy; so that the maximum level of demand satisfaction is achieved. Due to the nature of the disaster, we have used a fuzzy approach to estimate imprecise parameters. To cope with uncertain parameters, a possibilistic programming approach is developed. The worth of considering uncertainty in this study is clarified by supplementing the contribution with presenting a robust possibilistic programming approach and investigating the effect of using ICT to make an online connection between AAs and DCC to reduce the uncertainty degree and consequently better outcome that has been overlooked in existent literature on the distribution of relief items which is attempted in this study for the first time.

Accordingly, the contributions of this research are noteworthy as follows:

1- Integrating two main decisions in disaster relief distribution through considering procurement related to the selection of items to be loaded on vehicles; and vehicle routing problem simultaneously.
2- Using fuzzy logic to define cost and demand parameters and developing a possibilistic programming model to deal with the impreciseness of the mentioned parameters.
3- Improving the proposed possibilistic programming model through developing a robust possibilistic programming model; to overcome its weaknesses and shortcomings.
4- Investigating the effect of using online communication between the AAs with the DCC, in reducing demand uncertainty and consequently reducing costs and improving output, through the use of ICT.

3. Problem Definition

This paper presents an integrated procurement and vehicle routing problem for post-disaster distribution of relief items. In this model, to provide relief and distribute relief items from the depot to the AAs, homogeneous vehicles with limited capacity are used. This model creates the connection between vehicle routing and the issue of relief items procurement, to determine the best tour for vehicles as well as the best selection of relief items and their quantity to be loaded on vehicles. In fact, in this issue, the best selection of types of relief items and the best vehicle tour is determined by creating the optimal balance between the utility of each type of item and the volume they occupy, so that the maximum demand satisfaction in terms of volume and utility is achieved.

Due to the uncertain nature of the disaster, accurate estimates of the extent of damage and damaged areas and the demand for relief items are difficult and in some cases impossible. Therefore, in the information of the problem, some parameters such as demand, transportation cost, and penalty cost for unsatisfactory demand are considered uncertain using a triangular fuzzy membership function. To cope with the fuzziness and robustness, a robust possibilistic programming model is incorporated into the presented model.

3.1. The relationship between demand uncertainty and using ICT

In this paper, it is assumed that all of the vehicles are in contact with the DCC through GPS. It is also determined which AAs could be equipped with GPS to have online communication with the DCC via vehicles. Decisions about whether or not to equip AAs with GPS are made by considering the effect of GPS on reducing demand uncertainty such that, increasing the number of AAs with GPS online connection to the DCC, consequences reducing the uncertainty in estimating the demand for the mentioned areas, and as a result, the reducing the dissatisfaction of the demand. This issue balances the cost of GPS equipment with the cost of unsatisfactory demand, determining the best AAs for GPS equipment. GPS-enabled areas are connected to the DCC and provide online information on the number of relief items requested. In other words, this model determines the best points for equipping GPS by considering the costs of equipping GPS in AAs, so that the minimum dissatisfaction is achieved. Noteworthy, in this model, we seek to determine the best AAs for GPS equipment and the best selection of relief items and their quantity to be loaded on vehicles and the best vehicle tour simultaneously; So that the minimum total cost of the GPS equipment, transportation, and dissatisfaction is achieved.

In this research, it is assumed that the demand distribution is uncertainly determined by the triangular fuzzy membership function. So that if the GPS connection with the DCC is enabled in each one of AAs, the demand estimation is done with less uncertainty due to the online communication, and therefore the estimation of demand interval at the mentioned area becomes smaller. The demand parameter is considered uncertain and is a fuzzy number with a triangular membership function that is defined by its three prominent points, i.e. $\tilde{d} = (d^p, d^m, d^o)$.

As mentioned earlier, the presence of GPS at the AAs results in online communication with the DCC to estimate the value of demand of these areas with less uncertainty and smaller interval. As a result, in estimating the value of demand at each area, depending on whether it is equipped with GPS or not, the fuzzy parameters $\tilde{z}$ and $\widetilde{w}$ are considered for demand value respectively with a triangular membership function, that the former has a smaller interval than the latter, which indicates less uncertainty.

The demand parameter is determined in such a way that in areas where GPS connection is enabled, the value of demand is equal to $\tilde{z}$, and in areas where GPS connection is disabled, the value of demand is equal to $\widetilde{w}$. Therefore, because $\tilde{z}$ has a smaller interval than $\widetilde{w}$, the demand uncertainty will be less in the areas where GPS connection is enabled. Consequently, by considering this fact and the cost of equipping the GPS, the model endogenously determines which of the AAs should be equipped with GPS.

Generally demand parameter for each AA is defined as $\tilde{d} = (1-\beta)\widetilde{w} + \beta\tilde{z}$ Which β denotes the binary decision variable to determine whether the related AA is equipped with GPS or not; and $\tilde{z}$, $\widetilde{w}$ are defined as $\tilde{z} = (z^m, \varphi_z, \varphi'_z)$ and $\widetilde{w} = (z^m, \lambda\varphi_z, \lambda\varphi'_z)$ based on the method of displaying addressed by Pishvaee and Fazli Khalaf, (2016) where $\lambda > 1$; and parameters φ_z and φ'_z correspond lateral margins of the triangular fuzzy number $\tilde{z}$ and they can be defined as follows:

$$\varphi_z = z^o - z^m \quad (1)$$
$$\varphi'_z = z^m - z^p \quad (2)$$

Figure 1 represents the concept of determination of demand by $\tilde{z}$ and $\widetilde{w}$ parameters.

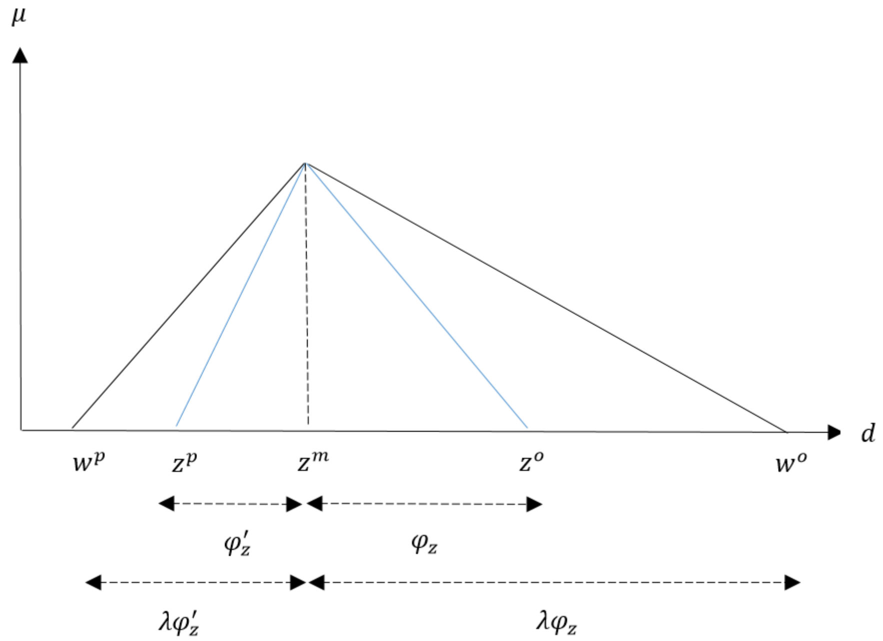

Figure 1. Determination of demand

Following the last explanations, the demand for each type of relief goods (displayed with p) at each AA (displayed with j) is formulated as follows:

$$\tilde{d}_{jp} = (1-\beta_j)\widetilde{w}_{jp} + \beta_j \tilde{z}_{jp} \qquad \forall j \epsilon N, p \epsilon P \qquad (3)$$

Which β_j denotes the binary decision variable to determine whether the related AA (displayed with j) is equipped with GPS or not.

4. Mathematical Modeling

4.1. Assumptions and Notations

The assumptions are as follows.

- A multi-commodity model with one depot is considered.
- Relief demand of each AA is provided by one vehicle.
- Each AA is visited by each vehicle at most once.
- Each type of relief item occupies a certain volume of vehicles.
- A homogeneous fleet with a limited capacity is considered.
- There is no limitation on the capacity of the depot.
- All AAs must be visited and assisted.
- Each vehicle leaves the depot after determining the policy for procurement and loading relief items and returns to it after delivering relief aid to several affected areas.
- All vehicles are equipped with GPS and have online communication with the DCC.

The notations of the proposed model are as follows.

Sets

N	Set of disaster nodes indexed by i, j
N'	Set of disaster nodes or depot indexed by i, j, $(N' = N \cup \{0\})$
P	Set of relief products indexed by p
V	Set of vehicles indexed by v

Parameters

$\tilde{c}_{ij}$	Transportation cost per unit distance from i to j
d_{ij}	Distance from i to j
ca	The capacity of each vehicle
o_p	Occupy percentage of product p
h	Cost of utilizing each vehicle
f_j	Cost of GPS equipment in affected area j
$\tilde{d}_{jp}$	Fuzzy demand of product p in affected area j

M	Sufficiently large number
$\tilde{p}_{jp}$	Penalty cost of unsatisfied demand for product p in affected area j
$\widetilde{w}_{jp}, \tilde{z}_{jp}$	Fuzzy parameters to determine demand

Decision variables

β_j	Equals 1 when affected area j is equipped with GPS connection, and is 0 otherwise
x_{ijv}	A binary variable, equal to 1 if affected area j is visited by vehicle v immediately after affected area i; and 0, otherwise
y_{jvp}	The quantity of product p, delivered to affected area j via vehicle v
l_{pv}	The quantity of product p, loaded in vehicle v
s_{jp}	Unsatisfied demand of product p in affected area j
e_{iv}	A dummy variable for sub-tour elimination

4.2. Objective function and constraints

$$Min\ Z = \sum_{j\epsilon N} f_j\beta_j + h\sum_{j\epsilon N}\sum_{v\epsilon V} x_{0jv} + \sum_{i\epsilon N'}\sum_{\substack{j\epsilon N' \\ i\neq j}}\sum_{v\epsilon V} \tilde{c}_{ij}d_{ij}x_{ijv} + \sum_{j\epsilon N}\sum_{p\epsilon P} \tilde{p}_{jp}s_{jp} \tag{4}$$

$s.t.$

$$(1-\beta_j)\widetilde{w}_{jp} + \beta_j\tilde{z}_{jp} \leq s_{jp} + \sum_{v\epsilon V} y_{jvp} \qquad \forall j\epsilon N, p\epsilon P \tag{5}$$

$$\sum_{j\epsilon N} x_{0jv} \leq 1 \qquad \forall v\epsilon V \tag{6}$$

$$\sum_{k\epsilon N} x_{0kv} = \sum_{i\epsilon N} x_{i0v} \qquad \forall v\epsilon V \tag{7}$$

$$\sum_{\substack{i\epsilon N' \\ i\neq j}}\sum_{v\epsilon V} x_{ijv} = 1 \qquad \forall j\epsilon N \tag{8}$$

$$\sum_{\substack{k\epsilon N' \\ k\neq j}}\sum_{v\epsilon V} x_{jkv} = 1 \qquad \forall j\epsilon N \tag{9}$$

$$\sum_{\substack{i\epsilon N' \\ i\neq j}} x_{ijv} = \sum_{\substack{k\epsilon N' \\ k\neq j}} x_{jkv} \qquad \forall j\epsilon N, v\epsilon V \tag{10}$$

$$y_{jvp} \leq M\sum_{\substack{i\epsilon N' \\ i\neq j}} x_{ijv} \qquad \forall j\epsilon N, v\epsilon V, p\epsilon P \tag{11}$$

$$\sum_{j\epsilon N} y_{jvp} \leq l_{pv} \qquad \forall v\epsilon V, p\epsilon P \tag{12}$$

$$\sum_{p\epsilon P} o_p l_{pv} \leq ca \qquad \forall v\epsilon V \tag{13}$$

$$e_{iv} - e_{jv} + |N|x_{ijv} \leq |N| - 1 \qquad \forall i, j\epsilon N, i\neq j, v\epsilon V \tag{14}$$

$$y_{jvp}, l_{pv}, s_{jp}, e_{jv} \geq 0 \qquad \forall i, j\epsilon N', i \neq j, p\epsilon P, v\epsilon V \tag{15}$$

$$\beta_j, x_{ikv} \epsilon \{0,1\} \qquad \forall i, k\epsilon N', j\epsilon N, i \neq k, v\epsilon V \tag{16}$$

Equation (4) defines the objective function which minimizes the cost of GPS connection of AAs, as well as the cost of utilizing each vehicle; penalty cost of unsatisfied demand, and transportation cost. Constraint sets (5) are subjected to demand satisfaction and dissatisfaction. Constraint sets (6) and (7) ensure the utmost number of exits and balance of departing from and entering to depot by each vehicle. Constraint sets (8), (9) guarantee that each AA is served once and via one vehicle. Constraint sets (10) ensure the balance of departing from and entering an AA by each vehicle. Constraint sets (11) enforce that the commodity flow by each vehicle is only applied to the routes through which the vehicle has passed. Constraint sets (12) guarantee that the maximum number of each commodity flow by each vehicle must not exceed the loaded quantity of the commodity in the vehicle. Vehicle limitation capacity is satisfied through constraint set (13). Constraint sets (14) satisfy sub-tour elimination. Constraint sets (15) and (16) apply binary or sign restrictions on the variables.

5. Possibilistic Programming Model

Possibilistic programming is a classification of fuzzy mathematical programming that deals with epistemic uncertainty and lack of knowledge about the exact value of parameters. (Pishvaee and Fazli Khalaf, 2016)

Since this paper deals with ill-known parameters (epistemic uncertainty), the proposed model belongs to the class of possibilistic programming models. Therefore, each ill-known parameter has its possibility distribution to represent the degree of their occurrence which is mainly represented based on available data of experts' knowledge. for more details, interested readers could refer to Mula et al. (2006) & Pishvaee and Torabi (2010).

To define the imprecise parameters, triangular possibility distribution is applied. It also should be noticed that expressions involving ill-known parameters like objective function (4) and constraint (5), should be substituted with their crisp value.

Based on the possibilistic programming approach presented by Jimenez et al. (2007) and Pishvaee and Torabi (2010) the equivalent crisp expressions for the objective function and demand constraint (constraint (5)) can be formulated as follows:

$$\begin{aligned} Min\ Z = \sum_{j\epsilon N} f_j \beta_j + h \sum_{j\epsilon N} \sum_{v\epsilon V} x_{0jv} + \sum_{i\epsilon N'} \sum_{\substack{j\epsilon N' \\ i\neq j}} \sum_{v\epsilon V} \left(\frac{c_{ij}^p + 2c_{ij}^m + c_{ij}^o}{4} \right) d_{ij} x_{ijv} \\ + \sum_{j\epsilon N} \sum_{p\epsilon P} \left(\frac{p_{jp}^p + 2p_{jp}^m + p_{jp}^o}{4} \right) s_{jp} \end{aligned} \tag{17}$$

$$\begin{aligned} (1-\beta_j) \left[\alpha \left(\frac{w_{jp}^o + w_{jp}^m}{2} \right) + (1-\alpha) \left(\frac{w_{jp}^p + w_{jp}^m}{2} \right) \right] \\ + \beta_j \left[\alpha \left(\frac{z_{jp}^o + z_{jp}^m}{2} \right) + (1-\alpha) \left(\frac{z_{jp}^p + z_{jp}^m}{2} \right) \right] \\ \leq s_{jp} + \sum_{v\epsilon V} y_{jvp} \end{aligned} \qquad \forall j\epsilon N, p\epsilon P \tag{18}$$

The parameter α denotes the confidence level of constraint embracing uncertain parameters $(0.5 < \alpha \leq 1)$ which is assigned by decision-make. However, according to Pishvaee et al. (2012), There are some weaknesses regarding basic possibilistic programming such that:

1- Determining the appropriate value of confidence level parameters for iterative experiments is time-consuming which is intensified with increasing the number of parameters.
2- Confidence level parameters are subjectively determined by the decision-makers and as a result, do not guarantee the optimality of the model.

3- This model disregards the possible violation of objective function from the planned value owing to the uncertainty of parameters.

To overcome the mentioned drawbacks, Pishvaee et al. (2012) developed their robust possibilistic programming models on the basic chance-constrained programming method in which the confidence level parameter is modified to a variable that is determined by the model.

5.1. Proposed robust possibilistic programming model

Robust optimization is known as a powerful and efficient approach due to its applicability to generate stable values for uncertain parameters (Rezaei-Malek et al., 2016). The expressions for the objective function and demand constraint is presented as follows based on Pishvaee et al. (2012):

$$\begin{aligned} Min\ Z = {} & \sum_{j\epsilon N} f_j\beta_j + h\sum_{j\epsilon N}\sum_{v\epsilon V} x_{0jv} + \sum_{i\epsilon N'}\sum_{\substack{j\epsilon N'\\ i\neq j}}\sum_{v\epsilon V}\left(\frac{c_{ij}^{p}+2c_{ij}^{m}+c_{ij}^{o}}{4}\right)d_{ij}x_{ijv} \\ & + \sum_{j\epsilon N}\sum_{p\epsilon P}\left(\frac{p_{jp}^{p}+2p_{jp}^{m}+p_{jp}^{o}}{4}\right)s_{jp} \\ & + \theta\left[\left(\sum_{i\epsilon N'}\sum_{\substack{j\epsilon N'\\ i\neq j}}\sum_{v\epsilon V} c_{ij}^{o}d_{ij}x_{ijv} + \sum_{j\epsilon N}\sum_{p\epsilon P} p_{ij}^{o}s_{jp}\right)\right. \\ & \left. - \left(\sum_{i\epsilon N'}\sum_{\substack{j\epsilon N'\\ i\neq j}}\sum_{v\epsilon V}\left(\frac{c_{ij}^{p}+2c_{ij}^{m}+c_{ij}^{o}}{4}\right)d_{ij}x_{ijv} + \sum_{j\epsilon N}\sum_{p\epsilon P}\left(\frac{p_{jp}^{p}+2p_{jp}^{m}+p_{jp}^{o}}{4}\right)s_{jp}\right)\right] \\ & + \delta\sum_{j\epsilon N}\sum_{p\epsilon P}\left[(1-\beta_j)\left(w_{jp}^{o} - \alpha\left(\frac{w_{jp}^{o}+w_{jp}^{m}}{2}\right) - (1-\alpha)\left(\frac{w_{jp}^{p}+w_{jp}^{m}}{2}\right)\right)\right. \\ & \left. + \beta_j\left(z_{jp}^{o} - \alpha\left(\frac{z_{jp}^{o}+z_{jp}^{m}}{2}\right) - (1-\alpha)\left(\frac{z_{jp}^{p}+z_{jp}^{m}}{2}\right)\right)\right] \end{aligned} \tag{19}$$

$$\begin{aligned} (1-\beta_j)&\left[\alpha\left(\frac{w_{jp}^{o}+w_{jp}^{m}}{2}\right) + (1-\alpha)\left(\frac{w_{jp}^{p}+w_{jp}^{m}}{2}\right)\right] \\ & + \beta_j\left[\alpha\left(\frac{z_{jp}^{o}+z_{jp}^{m}}{2}\right) + (1-\alpha)\left(\frac{z_{jp}^{p}+z_{jp}^{m}}{2}\right)\right] \leq s_{jp} + \sum_{v\epsilon V} y_{jvp} \end{aligned} \qquad \forall j\epsilon N, p\epsilon P \tag{20}$$

$$0.5 < \alpha \leq 1 \tag{21}$$

The third and the fourth terms of objective function indicate the average performance of the costs concerned with transportation and unsatisfactory based on the expected value of uncertain parameters. The fifth term adjusts the degree of optimality robustness. This term minimizes the maximum deviation over the expected performance of the objective function. The last term is applied to optimize the confidence level of the noted constraint and adjusts feasibility robustness relevant to the impreciseness of the parameters. In other words, it is embedded in the model to define the gap between the worst-case and selected value of the imprecise parameters. The parameters θ, δ determine the significance of these terms against the other terms and are called the coefficient of optimality and feasibility robustness respectively.

The proposed robust possibilistic programming model eliminates the drawbacks of the possibilistic programming model presented in the last section as the optimal value of confidence levels could be determined through it.

Notably, the presented model is non-linear due to the multiplication of variables in the last term of the objective function as well as the Constraint (20). Hence the model is linearized, and the proposed robust model is represented as follows:

$$
\begin{aligned}
Min\ Z = & \sum_{j\epsilon N} f_j\beta_j + h\sum_{j\epsilon N}\sum_{v\epsilon V} x_{0jv} + \sum_{i\epsilon N'}\sum_{\substack{j\epsilon N' \\ i\neq j}}\sum_{v\epsilon V}\left(\frac{c_{ij}^{p}+2c_{ij}^{m}+c_{ij}^{o}}{4}\right)d_{ij}x_{ijv} \\
& + \sum_{j\epsilon N}\sum_{p\epsilon P}\left(\frac{p_{jp}^{p}+2p_{jp}^{m}+p_{jp}^{o}}{4}\right)s_{jp} \\
& + \theta\left[\left(\sum_{i\epsilon N'}\sum_{\substack{j\epsilon N' \\ i\neq j}}\sum_{v\epsilon V} c_{ij}^{o}d_{ij}x_{ijv} + \sum_{j\epsilon N}\sum_{p\epsilon P} p_{ij}^{o}s_{jp}\right)\right. \\
& \left. - \left(\sum_{i\epsilon N'}\sum_{\substack{j\epsilon N' \\ i\neq j}}\sum_{v\epsilon V}\left(\frac{c_{ij}^{p}+2c_{ij}^{m}+c_{ij}^{o}}{4}\right)d_{ij}x_{ijv} + \sum_{j\epsilon N}\sum_{p\epsilon P}\left(\frac{p_{jp}^{p}+2p_{jp}^{m}+p_{jp}^{o}}{4}\right)s_{jp}\right)\right] \\
& + \delta\sum_{j\epsilon N}\sum_{p\epsilon P}\left[(1-\beta_j)w_{jp}^{o} - (\alpha-\gamma_j)\left(\frac{w_{jp}^{o}+w_{jp}^{m}}{2}\right) - (1-\beta_j-\alpha+\gamma_j)\left(\frac{w_{jp}^{p}+w_{jp}^{m}}{2}\right)\right. \\
& \left. + \beta_j z_{jp}^{o} - \gamma_j\left(\frac{z_{jp}^{o}+z_{jp}^{m}}{2}\right) - (\beta_j-\gamma_j)\left(\frac{z_{jp}^{p}+z_{jp}^{m}}{2}\right)\right]
\end{aligned}
\tag{22}
$$

$s.t.$

$$
\begin{aligned}
(\alpha-\gamma_j)\left(\frac{w_{jp}^{o}+w_{jp}^{m}}{2}\right) + (1-\beta_j-\alpha+\gamma_j)\left(\frac{w_{jp}^{p}+w_{jp}^{m}}{2}\right) & \\
+ \gamma_j\left(\frac{z_{jp}^{o}+z_{jp}^{m}}{2}\right) + (\beta_j-\gamma_j)\left(\frac{z_{jp}^{p}+z_{jp}^{m}}{2}\right) & \\
\le s_{jp} + \sum_{v\epsilon V} y_{jvp} & \qquad \forall j\epsilon N, p\epsilon P
\end{aligned}
\tag{23}
$$

$$\gamma_j \le M\beta_j \qquad \forall j\epsilon N \tag{24}$$

$$\gamma_j \ge M(\beta_j - 1) + \alpha \qquad \forall j\epsilon N \tag{25}$$

$$\gamma_j \le \alpha \qquad \forall j\epsilon N \tag{26}$$

$$\gamma_j \ge 0 \qquad \forall j\epsilon N \tag{27}$$

$$0.5 < \alpha \le 1 \tag{28}$$

Constraints (6) to (16)

Where $\gamma_j = \alpha\beta_j$ ($\forall j\epsilon N$) is an auxiliary variable added to linearize the model.

6. Case Study

Tehran is the most populated city of Iran with the majority of social, political, financial, and cultural important centers (Bozorgi-Amiri and Khorsi, 2015). In the last decades, a large number of disasters such as floods and earthquakes have occurred in this city. Since there are many active faults across the city such as the Mosha fault, Rey fault, North fault, and …, it is highly vulnerable to earthquake disasters.

Tehran consists of 22 districts, among which the 7th district contains many important organizations and centers. Moreover, it is a central district and contains military organs, and; the existence of worn and old building structures in this district clarifies the significance of disaster threats in this district. Therefore, a case problem is conducted in this district to study relief operations such as routing, procurement, and relief distribution to tackle the occurrence of an earthquake. It is divided into 5 zones and has a population of 312194 according to the last census data. Figure 2 represents the considered district and the faults across Tehran.

The AAs in the 5 zones of the 7th district and their affected population by the disaster are presented in Table 1. Since the first, the second and the fifth zones consist of more old buildings and worn structures, the coefficient of the population in mentioned zones to estimate the affected population, is bigger than the one in the third and the fourth zones. There is a Disaster Shed in district 7 which is assumed to be the depot. The real distances between AAs, as well as their distances to the depot, are extracted from Google Maps. The parameters related to demand are assumed to be $\lambda = 10, \varphi_z = \varphi'_z = 50$, and the fuzzy numbers of demand parameters for each commodity related to the AAs are represented in Table 2. As it was explained in subsection 3.1, pessimistic and optimistic values of $\tilde{z}$ are obtained by subtracting φ_z from the most likely prominent points, and adding φ'_z to the most likely prominent points, respectively. For pessimistic and optimistic values of $\tilde{w}$, the lateral margins are $\lambda\varphi_z$ and $\lambda\varphi'_z$.

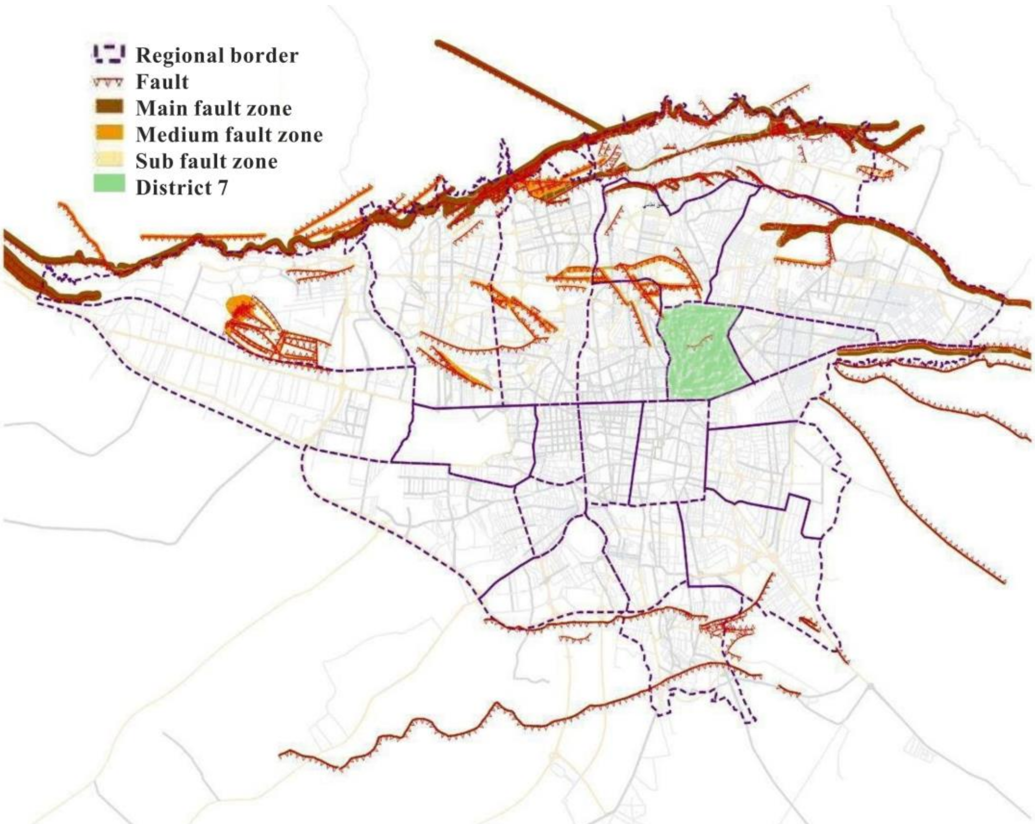

Figure 2. Map of faults and fault zones of Tehran

Table1. The considered affected areas with their population

Zones	AA	Affected population
1	Municipality of the First Zone	1707
2	Municipality of the Second Zone	1327
3	Municipality of the Third Zone	474
4	Imam Khomeini Mosalla	545
5	Museum of the Qasr Prison	1660

Table 2. Fuzzy numbers of demand parameters for each commodity

Zones	$\tilde{z} = (z^p, z^m, z^o)$		$\widetilde{w} = (w^p, w^m, w^o)$	
	Mineral water	**Canned foods**	**Mineral water**	**Canned foods**
1	(3364,3414,3464)	(5071,5121,5171)	(2914,3414,3914)	(4621,5121,5621)
2	(2604,2654,2704)	(3931,3981,4031)	(2154,2654,3154)	(3481,3981,4481)
3	(898,948,998)	(1372,1422,1472)	(448,948,1448)	(922,1422,1922)
4	(1040,1090,1140)	(1585,1635,1685)	(590,1090,1590)	(1135,1635,2135)
5	(3270,3320,3370)	(4930,4980,5030)	(2820,3320,3820)	(4480,4980,5480)

A Fleet routing for four homogeneous trucks with a capacity of 3000 kg is used and it is assumed that each mineral water and canned food occupy 0.75 and 0.25 of the weight of a vehicle respectively. It is assumed that the coefficient of the optimality and feasibility robustness is equal to $\theta = 10, \delta = 50$ respectively.

6. Results

The proposed model was executed utilizing GAMS 2٤.١.2 software with CPLEX solver on a computer with Intel Core i7, 3.2 GHz CPU, 6GB RAMDDR3 under Windows 10 x64 with 75 seconds run time with the objective function value of 5237701 units of money. The model has employed all four vehicles for distribution. Among the 5 zones, three zones have been selected to be equipped with GPS. Therefore, the β_j variable for the 5 zones is represented as $\beta_j = (1,1,0,0,1)$. It means that the Municipality of the first and second zone as well as the Museum of the Qasr Prison are selected to be equipped with GPS. Moreover, the confidence level variable α has taken its minimum possible value equal to 0.6.

The route of relief vehicles is demonstrated in Figure 3. Besides, the number of relief items loaded in each vehicle as well as the satisfied and unsatisfied demand for each relief commodity are presented in Table 3 and Table 4 respectively.

Table 3. The output variables of the model

Vehicles	Loaded quantity		Created tours
	Mineral water	**Canned food**	
1	2338	4985	Disaster Shed- Museum of the Qasr Prison- Disaster Shed
2	2947	3157	Disaster Shed- Imam Khomeini Mosalla- Municipality of the Third Zone- Disaster Shed
3	2291	5126	Disaster Shed- Municipality of the First Zone- Disaster Shed
4	2671	3986	Disaster Shed- Municipality of the Second Zone- Disaster Shed

Table 4. The other output variables of the model

Affected areas	Satisfied demand		Unsatisfied demand	
	Mineral water	**Canned food**	**Mineral water**	**Canned food**
Museum of the Qasr Prison	2338	4985	986	-
Imam Khomeini Mosalla	1140	1685	-	-
Municipality of the First Zone	2291	5126	1127	-
Municipality of the Second Zone	2291	5126	-	-
Municipality of the Third Zone	1807	1472	--	-

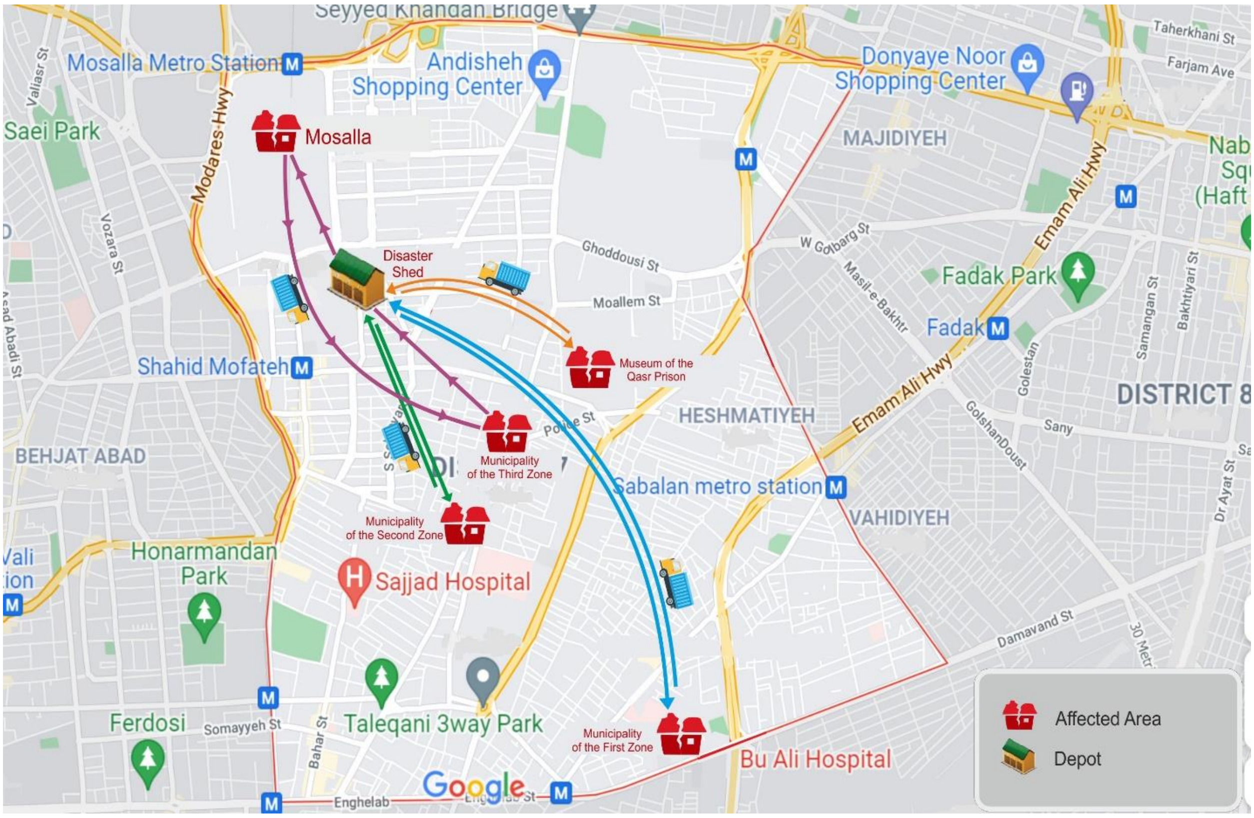

Figure 3. The optimal route of relief vehicles

As an example from the created routes of Table 3 and Table 4, the first vehicle loaded 2338 required mineral water and 4985 required canned foods and commenced its route from the depot; arrived at Museum of the Qasr Prison; unloaded all of the loaded relief items to this area; then returned to the depot. According to the demand of relief items related to the Museum of the Qasr Prison, 986 slacks on mineral water and no slack on canned foods are recorded in this affected area. To analyze the sensitivity of the model parameters, we have compared the output results by changing some parameters. For instance, as the capacity of vehicles increases, the model improves and the value of the objective function decreases. Figure 4 demonstrates this relationship.

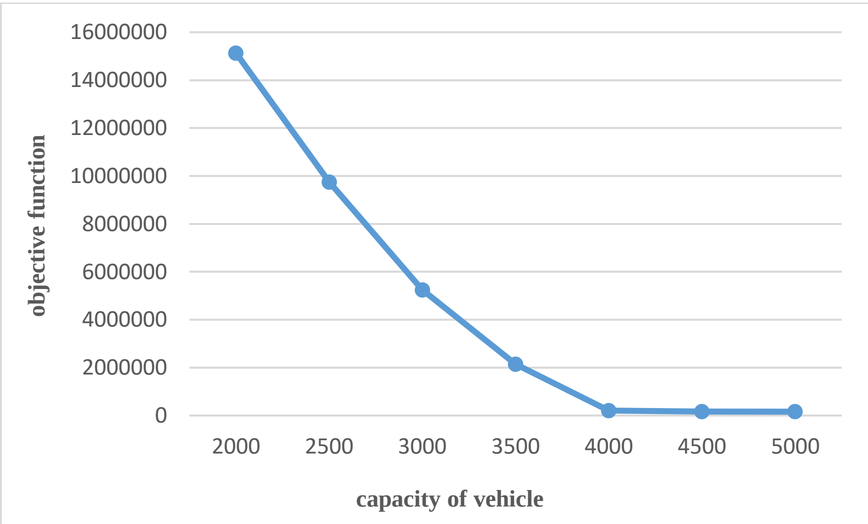

Figure 4. The impact of increasing capacity of vehicles on the objective function

We have performed the sensitivity analysis on the coefficient of the feasibility robustness (δ). By increasing this parameter up to 620, the confidence level variable α has been fixed and unchanged equal to 0.6. This value will be equal to 0.785 for δ values from 620 to 910 and is equal to 1 for δ values greater than 910. Also, the results of sensitivity analysis on the coefficient of the feasibility robustness (δ) show that with the increase of this parameter, the objective function has also increased. Figure 5 represents the impact of increasing the coefficient of the feasibility robustness on the confidence level variable.

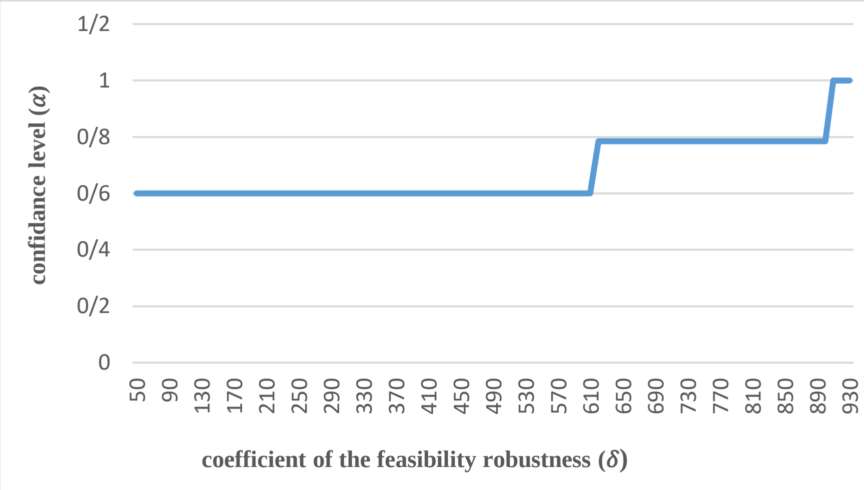

Figure 5. The impact of increasing δ on the confidence level variable

The results of doing sensitivity analysis on the coefficient of the optimality robustness (θ) are also represented in Figure 6 which demonstrates the impact of increasing it on the objective function to be increased.

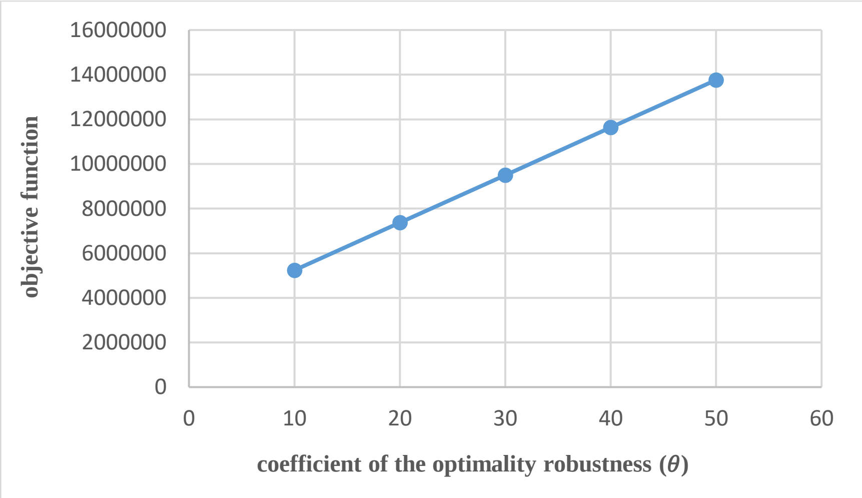

Figure 6. The impact of increasing θ on the objective function

To validate the proposed model, we have compared it to the model without considering ICT. The comparison results are shown in Table 5.

Table 5. Results of comparison proposed model to the model without ICT

δ	With ICT				Without ICT	
	β_j	α	Objective function	Runtime	Objective function	Runtime
50	(1,1,0,0,1)	0.6	5237701	75	5535068	55
90	(1,1,1,1,1)	0.6	5304701	77	5715068	55
620	(1,1,1,1,1)	0.785	5542585	80	8100068	57
910	(1,1,1,1,1)	1	5645901	82	9398401	59

The results of the comparison show that the proposed model (considering ICT) achieves a better result than the model without considering ICT. Furthermore, by increasing δ the difference between objective functions increases and for δ values greater than 90, the model has selected all 5 zones to be equipped with GPS. Figure 7 corresponds to the results of comparing two models.

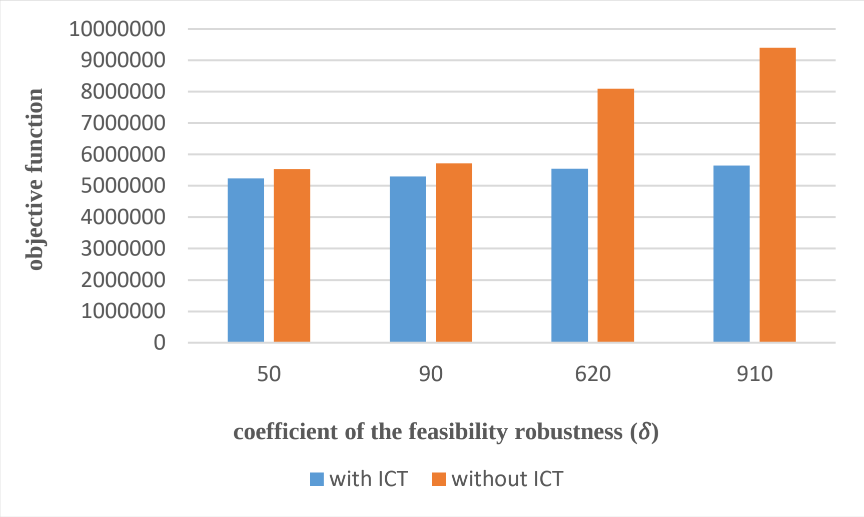

Figure 7. Comparison of the proposed model with the model without ICT consideration

7. Conclusions

Due to increasing the importance of disaster in recent years, this paper presented an integrated model of procurement and routing of vehicles after the disaster to distribute relief items. Since unpredictable events may occur in the early hours or days of a disaster, the nature of disaster is uncertain. In this paper, the cost parameters, as well as the demand for relief items, are considered fuzzy parameters. Additionally, the impact of existing information and communication technologies such as GPS is investigated which allows communication between the affected areas with the disaster coordination center. This connection must be made through vehicles, hence rescue vehicles must also be equipped with GPS. In this issue, we have examined the possibility of enabling the affected areas to GPS. This model endogenously determines which of the affected areas are selected to be equipped with GPS, due to the costs of equipping GPS and the effect it has on reducing demand uncertainty and thus reducing demand dissatisfaction. A robust possibilistic programming model is presented, and eventually, the results of the model are examined on a real case study in district 7 of Tehran. The results show that the existence of ICT has a positive and significant effect on reducing relief costs. In order to investigate the model in real-world applications and practical implications, it is important to observe that in the occurrence of an earthquake due to its uncertain and unpredictable nature, unexpected events such as aftershocks in the early hours after a disaster, network failure, road disruption, and collapsing the buildings that have been destroying since the early hours of the disaster which causes demand for relief items to be increased, may occur in future time periods. Hence the uncertainty in demand rate is a rational and real-world assumption. Moreover, at the beginning of disaster response, there is insufficient information about the demand for relief resources, exact locations, or readily available routes. Therefore, relief services face problems such as rapid change of information, urgent requests and poor quality of previous information which clarify the importance of using ICT in communicating the updated information between the affected areas and the disaster coordination center. This paper may be developed by further researches with consideration of dynamism in the information of the model such as the demand to be changeable over time. Taking into consideration of large-scale problem would be another suggestion that needs to use metaheuristic approaches to solve it due to the complexity of the vehicle routing problem. Moreover, taking into account relief time assumption or time window consideration is suggested for future research of this study.

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