Optimization of an evacuation plan with uncertain demands using fuzzy credibility theory and genetic algorithm

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A B S T R A C T

Evacuation planning is an important activity in disaster management. Due to the sudden occurrence of disasters, evacuation should be preplanned. It is necessary for evacuation plan to be as close as possible to a real evacuation operation. However, evacuation planning is challenging because of inherent uncertainty in required information. One important source of uncertainty in evacuation is the uncertainty in evacuation demands. This paper presents an evacuation vehicle routing problem to design evacuation routes for public vehicles. In this problem, demand (number of evacuees) at each pick-up point is introduced as a fuzzy number and the assignment of the pick-up points to the vehicle routes happens based on a credibility preference index. A genetic algorithm based on fuzzy credibility theory is designed to optimize the problem. The optimum parameter set for genetic algorithm is obtained by Taguchi experimental design. The presented problem and algorithm are applied on a part of Tehran transportation network. The impact of credibility preference index on the achieved solutions is evaluated and its best value is determined for the case study. Moreover, different tests are implemented to analyze and discuss the influence of uncertainty level on the final results. © 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Recent occurrence of disasters (such as earthquake, flood, hurricane, chemical spill, and nuclear accident) in urban areas shed light on the importance of emergency management. Although the probability of disaster occurrence may be relatively low, its tragic consequences put emphasis on the necessity of emergency management. Al-hurricane, chemical spill, and nuclear accident) in urban areas.

Public transit system can play a crucial role in improving the level of evacuation service [33,40,32,15]. Naghawi and Wolshon [22] showed that public-transit buses were able to increase the total number of evacuated people and had a minimum impact on traffic when they were routed to arterial evacuation routes. Besides, Chen and Chou [4] suggested that the clearance time of an evacuation can be improved substantially if more people choose to evacuate through the public transit system. It should be noticed that public transit-based evacuation plan should be well-organized to aid the emergency management.

Evacuation planning is a challenging complex problem due to the inherent uncertainties in the information that is used for decision making during emergency situations. In a public transport-based evacuation, information on evacuees and their pick-up locations, evacuation vehicles and transportation network may be uncertain, incomplete and erroneous. There can be uncertainty in the number of vehicles, their available capacity and their original location. In the transportation network, uncertainty may be in the term of limited link capacity, travel time as well as limited network connectivity. Additionally, unpredictability of disaster occurrence time and its severity are other factors that introduce uncertainty in the evacuation planning (Fig. 1).

Most of the research undertaken on evacuation planning...
ignores the information uncertainty. However, it is very unlikely that an actual evacuation operation follows the same direction as in predetermined plan. Hence, an optimal evacuation plan should consider uncertainties in order to maintain a high probability of the actual evacuation to be as close as possible to the planned one.

This paper presents an evacuation vehicle routing problem (EVRP) using public vehicles in urban areas. The source of uncertainty in this problem is the evacuation demand. In the proposed methodology, demand (number of evacuees) at each evacuation pick-up point is introduced as a fuzzy variable. Fuzzy credibility theory is used to deal with this uncertainty and a genetic algorithm (GA) based on this theory is designed to solve the stated problem. The algorithm parameters are optimized using the robust parameter setting approach proposed by Taguchi [36]. To evaluate the obtained solutions, a stochastic simulation method is employed. As far as the authors know, this is the first work in the literature of the evacuation planning which uses fuzzy credibility theory to model the assignment of uncertain demands to the vehicle routes.

In this paper, a literature review is presented in Section 2. Section 3 reveals the authors’ motivation for the research. Section 4 discusses the necessary principles underlie the proposed methodology. The methodology is represented in Section 5. Section 6 describes a case study. Taguchi experimental design is followed in Section 7. The obtained results and the related discussion are presented in Section 8 and the conclusions are explained in Section 9.

2. Literature review

A few studies have been conducted on evacuation planning under demand uncertainty. These can be categorized in three main groups based on the optimization approach employed including: simulation optimization, stochastic programming and robust optimization [16].

2.1. Simulation optimization

Simulation optimization is an attractive research area. It can be defined as the process of finding the best input variable values from all possibilities without explicitly evaluating each possibility. In an iterative process, the output of a simulation model is used by an optimization strategy as a feedback on progress of the search for the optimal solution [3].

In a research by Pel et al. [27], a structured and comprehensive sensitivity analysis identifies and quantifies the impact of variations in travel demand and network supply in the case of evacuation. In sensitivity analysis, the macroscopic evacuation traffic simulation model, Evacuation of Vehicles using Assignment with Queuing (EVAQ) [26], is applied in which aspects such as trip generation, departure rates, route flow rates, road capacities, and maximum speeds are systematically varied. Departure and route flow rates are found to have a substantial nonlinear impact on network conditions and arrival pattern, particularly when the network load is relatively high, whereas trip generation and road capacities have a smaller quasilinear impact.

Huibregtse et al. [14] presented an approach to optimize evacuation measures which consist of instructions and information to evacuees and traffic management measures under uncertainty. The sources of uncertainty in this evacuation problem are related to the number of evacuees, their behavior and the hazard characteristics (location, time, and intensity). The uncertainty is translated into scenarios which could occur. Although this approach has some restrictions for real applications, the case study shows the usefulness of dealing with uncertainty in the evacuation problem.

The process of simulation optimization is often slow even for a small problem, while most of real-world problems are large and need to be solved in a reasonable time.

2.2. Stochastic programming

In order to tackle problems that involve uncertainty, stochastic programming finds a solution which is feasible for all such data and optimal in some sense considering that probability distributions of the data are known. The goal here is to find some policy that is feasible for all (or almost all) the possible data instances and maximizes the expectation of some function of the decisions and the random variables [34].

Yazici and Ozbay [45,44] followed the stochastic programming approach in their studies. Yazici and Ozbay [45] suggested a more realistic approach to evacuation planning by capturing the probabilistic nature of link capacities due to the impacts of disasters. A cell transmission model (CTM) based system optimal dynamic traffic assignment (SODTA) formulation is extended by introducing
probabilistic capacity constraints. The model determines the change in capacity requirements and desirable shelters locations as a result of link capacity changes during evacuation. The results showed that introducing probabilistic link capacities can adjust the overall flow in the network as well as the shelter utilization. In this study, the evacuation demand is assumed to be known.

Yazici and Ozbay [44] added the other major source of uncertainty, namely, randomness in evacuation demand in the proposed analytical system-optimal dynamic traffic assignment model. The problem is modeled on the basis of two stochastic modeling approaches considering the problem’s constraints, namely, individual chance constraints and joint chance constraints. This model enables evacuation planners to obtain results that can be interpreted through well-understood reliability measures.

Ng and Waller [24] presented a CTM-based model that considers both road capacities as well as demand uncertainties. This model does not require the assumption that probability distributions are known explicitly and a novel distribution-free approach is used to provide probabilistic guarantees on the resulting evacuation plan by allowing for infeasibilities with a pre-specified tolerance level. This model allows determining the amount of demand inflation/supply deflation necessary to ensure a user-specified reliability level and provide a good estimate of realized evacuation time.

Das and Hanaoka [7] developed a humanitarian disaster relief inventory model that assumes a uniformly distributed function in both lead–time and demand parameters. A stochastic linear model under several constraints is proposed to introduce uncertainty in humanitarian logistics. The model creates a joint distribution of lead–time–demand (LTD) and provides the prescription for inventory ordering policy via reorder quantity and reorder level. The sensitivity analysis shows that a stochastic model is superior to a deterministic model in term of total expected cost. The results revealed valuable direction for humanitarian relief planning efforts and future research.

Stochastic programming assumes that the probability distribution of uncertain data is known deterministically and is unaffected by the decisions that are taken during the process. However, it is difficult and costly to fit a probability distribution to the real-world data due to the insufficient information. Moreover, handling problems with stochastic programming approach is sometimes complex.

2.3. Robust optimization

A more recent approach for optimization under uncertainty is robust optimization, in which the uncertainty model is not stochastic, but rather deterministic and set-based [2]. In this approach, random variables are modeled as uncertain parameters belonging to a convex uncertainty set and the decision-maker protects the system against the worst case within that set [1].

In this category, Yao et al. [43] admitted the importance of demand uncertainty in evacuation and developed a robust linear programming model where hard constraints are guaranteed within an appropriate uncertainty set. Furthermore, it is showed that a robust solution outperforms a nominal deterministic solution in both quality and feasibility.

Kulshrestha et al. [17] presented a robust approach for determining optimum locations of public shelters and their capacities considering the demand uncertainty associated with the number of people using the public shelters during evacuation. The proposed model is formulated as a mathematical program with complementarity constraints and is solved by a cutting-plane scheme. A numerical example demonstrates that robust plans are able to achieve nearly the same level of performance at a significant lower cost.

Ren et al. [31] combined the processes of evacuation route planning and traffic signal design into an integrated model for emergency evacuations considering uncertain background travel demands. It is assumed that background travel demands belong to an ellipsoidal likelihood region whose parameters are determined by a singly constrained gravity mode. Based on the concept of robust optimization, the problem is formulated as a bi-objective bi-level model, where evacuation flows and traffic signals are variables. NSGA-II was used as the solution algorithm. An example illustrates the validity of the algorithm and a case study shows the applicability of this algorithm.

In order to better reflect the real world evacuation and improve the efficiency of large-scale evacuation, Hua et al. [13] proposed a network aggregation method and a bi-level optimization control method. The network aggregation method indicates the uncertain evacuation demand on the arterial sub-network and balances accuracy and efficiency by refining the local road sub-networks. The numerical results from optimizing a real large-scale evacuation network confirm the validity and usefulness of the proposed methods.

Qu and Yu [30] formulate the evacuation problem as robust model in which the resulting evacuation solutions are immune to the demand uncertainty without known probability distributions in the complex emergency evacuation context. The performance of three robust models namely box uncertainty set, ellipsoidal uncertainty set and polyhedral uncertainty set, are evaluated using a small-sized evacuation network. Results showed the robust solutions are preferable and it is convenient for planners to obtain the feasible solutions within the prescribed uncertainty set. Authors also claimed that planners could still find out a desirable evacuation solution with a smaller violation probability in the case of actual demand exceeds the given set.

Goerigk et al. [11] considered a robust bicriteria model for the regional evacuation with the help of buses which considers both the evacuation time, and the vulnerability of the schedule to changing evacuation circumstances. Its applicability is increased by its possibility to handle complex, non-linear uncertainty sets. An iterative solution algorithm was presented that alternately solves the robust problem for a limited set of scenarios, and generates new scenarios from the uncertainty set. The result showed that the robust problem can be solved within reasonable computation times.

While robust optimization approach provides partial guarantees for solution in the terms of quality and efficiency, its applicability is restricted and it may add to the complexity of problem.

3. Motivation

The optimization approaches discussed in the last Section have some limitations in the terms of computation time, complexity and initial information. These limitations may decrease their applicability to real-world scenarios.

The theory of fuzzy set is successful in modeling problems that contain an element of uncertainty related to subjectivity, ambiguity and vagueness [38]. This theory involves with fuzzy sets, the elements of which have degrees of membership. Fuzzy set theory permits the gradual assessment of the membership of elements in a set.

Using fuzzy theory, one can easily estimate the uncertain element based on expert judgment, experience or historical information. So, it does not slow down the optimization process by any iterative approaches. Besides, it is relatively simple to model uncertain data using fuzzy sets and it does not increase the complexity of problem. This is particularly true about
epistemological data (e.g., maximum capacities of water intakes, water pollution indices, and demands), due to high subjectivity in the estimation. The experts accepted expressing this data in the terms of tolerance intervals with a most-possible value and decreasing possibility for other values within the interval. In this case, the modeling of uncertainty using fuzzy numbers was quite natural. Furthermore, contrary to stochastic programming, fuzzy theory does not need precise information to define different scenarios with associated subjective probabilities [35].

There are a number of evacuation studies which used a fuzzy logic approach. Most of them concentrate on using fuzzy logic in modeling evacuees’ behavior in decision making (e.g., [8,21,23,12]). However, there are some other studies that use this theory for generating evacuation scenarios or presenting the relation between evacuation population and places (e.g., [9,39,29]). To the best of the author’s knowledge, none of these studies considered the assignment of uncertain demand to public vehicle routes for an evacuation operation. However, in most real-world cases precise information about evacuation demands and vehicles’ capacity are not available.

4. Basic principles

In this section, the basic principles which underlie the proposed methodology are described. In Section 4.1 the details of fuzzy credibility theory is presented and then, the general process of GA is explained in Section 4.2.

4.1. Fuzzy credibility theory

In real world, many phenomena show a degree of vagueness that cannot be well described with crisp sets of class boundaries. Zadeh [46] introduced fuzzy sets, a mathematical theory, to better deal with these phenomena and express them with degrees of membership to a fuzzy set. Zadeh [47] proposed the possibility theory to measure a fuzzy event and thereafter, Liu [19] founded credibility theory, a branch of mathematics that studies the behavior of fuzzy phenomena. The principles of credibility theory: possibility, necessity and credibility are described below [19,20].

Definition 1. Let θ be a non-empty set, and P(θ) be the power set of θ. Each element in P(θ) is called an event and ∅ is an empty set. For each A ∈ P(θ), there is a non-negative number, Pos(A), which indicates the possibility that A will occur (1):

\[
\begin{align*}
\text{Pos}(\varnothing) & = 0, \\
\text{Pos}(\theta) & = 1, \\
\text{Pos}\left( \bigcup_k A_k \right) & = \sup_k \text{Pos}(A_k), \quad \forall \{A_k\} \in P(\theta)
\end{align*}
\]

(1)

The triplet (θ, P(θ), Pos) is called a possibility space, and the function Pos(·) is referred to as a possibility measure.

Definition 2. Let (θ, P(θ), Pos) be a possibility space, and A be a set in P(θ). Then the necessity measure of A is defined by (2), where A′ is the complement of A:

\[
\text{Nec}(A) = 1 - \text{Pos}(A')
\]

(2)

Definition 3. Let (θ, P(θ), Pos) be a possibility space, and A be a set in P(θ). Then the credibility measure of A is defined by (3):

\[
\text{Cr}(A) = \frac{1}{2} \left( \text{Pos}(A) + \text{Nec}(A) \right)
\]

(3)

If μ_E(x) is the membership function of the fuzzy variable E, then the possibility, necessity, and credibility of fuzzy event {E ≥ r} can be represented respectively by (4), (5) and (6):

\[
\begin{align*}
\text{Pos}\left\{ \hat{E} \geq r \right\} & = \sup_{x \geq r} \mu_E(x), \\
\text{Nec}\left\{ \hat{E} \geq r \right\} & = 1 - \sup_{x \geq r} \mu_E(x), \\
\text{Cr}\left\{ \hat{E} \geq r \right\} & = \frac{1}{2} \left( \text{Pos}\left\{ \hat{E} \geq r \right\} + \text{Nec}\left\{ \hat{E} \geq r \right\} \right)
\end{align*}
\]

(4) \hspace{1cm} (5) \hspace{1cm} (6)

As it is showed, credibility of a fuzzy event is equal to the average of its possibility and necessity. The fuzzy event must hold, if its credibility is 1, and fail, if its credibility is 0.

4.2. Genetic algorithm

GA [10] is a population-based evolutionary metaheuristic. It starts with a population of solutions. The parameter PopulationSize controls the number of solutions in the population. The initial solutions can be generated randomly or using a heuristic. Each individual solution is represented by a specific encoding that depends on the nature of problem. The solutions in population are evaluated based on a cost function to determine their fitness. Then, some of them are selected by a selection operator (fitter solutions have more chance to be selected) as the parents of the next generation. Crossover is a mechanism for generating new population. In the crossover, each pair of selected parents generates two new offsprings (solutions). Mutation is another operator that implements minor change in the solution in order to explore new regions of the solution space and add diversity to the population Crossover and mutation operators are applied according to predefined probability parameters called CrossoverRate and MutationRate, respectively.

The new solutions form the new population. This procedure is repeated for a number of generations and at last, the fitter solution in the population is accepted as the final solution. The parameter GenerationNumber controls the number of generations GA proceeds. For a more comprehensive study on GA, it is referred to Vaira and Kurasova [42].

5. Methodology

In this section, details of the proposed methodology are presented. The EVRP model is clarified in Section 5.1. Sections 5.2 and 5.3 are devoted to describe the fuzzy credibility theory and GA to solve the EVRP, respectively.

5.1. Model description

In this paper, the scenario of a public transit-based evacuation operation in an urban area is considered. In this case, people who rely on public vehicles for evacuation are gathered in pick-up points. Conventional bus-stops are considered as pick-up points. Then, evacuees are transferred to the closest shelter outside the affected area by public vehicles. It is assumed that sufficient number of vehicles is provided for this purpose.

The evacuation problem is modeled based on vehicle routing problem (VRP) [6]. In the classic version of VRP, the objective is to design a set of routes in which vehicles start their trip from a depot, visit customers to serve the demands and finally, return to depot (Fig. 2). Routes should be designed in the least cost manner. The cost is usually interpreted as total distance or total travel time calculated in Euclidean space.

In this paper, VRP is extended to EVRP. In EVRP, each vehicle starts its trip from a depot, visits some pick-up points to pick up evacuees and when its capacity is full, departs to the closest shelter (Fig. 3). The pick-up points should be assigned to the
vehicle routes in a way that the total travel time is minimized. This leads to the reduction of the evacuation time. Total travel time is calculated on transportation network model.

In EVRP, it is assumed that vehicles are the same with a limited initial capacity, while they are empty when they leave depot and start their trip.

The mathematical formulation of EVRP is described below. The problem can be presented as a graph $G(N,E)$ in which $N$ and $E$ represent the edges and the nodes, respectively. Nodes are comprised of depot, pick-up points and shelters. Edges present the path with the shortest travel time between the nodes on the transportation network. In the following mathematical representation, subsets of nodes are used. To facilitate the model presentation, notations used hereafter are summarized below:

- $N_{DP}$: Set of depot and pick-up points.
- $N_{SP}$: Set of shelters and pick-up points.
- $N_{P}$: Set of pick-up points.
- $D$: Depot.
- $K$: Set of vehicles.
- $i, j$: Node index.
- $k$: Vehicle index.
- $C$: Initial vehicle capacity.
- $t_{ij}$: Travel time between node $i$ and $j$.
- $n$: Number of pick-up points.
- $E_k$: Number of evacuees boarded on vehicle $k$.
- $E_i$: Number of evacuees at pick-up point $i$.
- $u_k$: Free variable used in the subtour elimination constraint.
- $x_{ijk}$: Decision variable: 1, if vehicle $k$: passed from node $i$ to node $j$. Otherwise 0.

$$
\text{min } (Z = \sum_{i \in N_{DP}} \sum_{j \in N_{DP}} \sum_{k \in K} t_{ij} \cdot x_{ijk}).
$$

$$
\sum_{i \in N_{DP}} \sum_{j \in N_{DP}} x_{ijk} - \sum_{j \in N_{DP}} x_{ijh} = 0 \quad \forall k \in K, \ h \in N_{P}.
$$

$$
u_k - u_k + n \cdot x_{ijk} \leq n - 1 \quad \forall i, j \in N_{P}, \ k \in K.
$$

$$
\sum_{i \in N_{P}} \sum_{j \in N_{P}} x_{ijk} \cdot E_j \leq C - E_k \quad \forall k \in K.
$$

$$
\sum_{j \in N_{P}} x_{ijk} \leq 1 \quad \forall k \in K, \ i = D.
$$

$$
\sum_{j \in N_{P}} \sum_{k \in K} x_{ijk} = 1 \quad \forall i \in N_{P}.
$$

$$
\sum_{i \in N_{P}} \sum_{k \in K} x_{ijk} = 1 \quad \forall j \in N_{P}.
$$

$$
x_{ijk} = \{0, 1\} \quad \forall i \in N_{DP}, \ j \in N_{DP}, \ k \in K.
$$

Eq. (7) represents the objective function. This function minimizes the total travel time passed by all the vehicles from depots (at the beginning of the trip) or pick-up points to the (another) pick-up points or shelters (at the end of the trip). Eq. (8) describes the conservation flow constraint in which for each pick-up point,
the entering vehicle must eventually leave it. Eq. (9) is used for subtour elimination in VRP problem. Eq. (10) states the vehicle capacity constraint. In this equation, \( C - \sum_{i=1}^{m} e_i \) defines the available capacity and based on this constraint, this capacity should not be exceeded. Eq. (11) guarantees that each bus can be utilized at most once during the evacuation period. In other words, each vehicle has to do only one trip starts from a depot and ends at a shelter through the evacuation period. Eqs. (12) and (13) ensure that each pick-up point can be visited by one vehicle. That is, the number of evacuees in each pick-up point should not be split to be picked up by more than one vehicle. Eq. (14) describes the binary decision variable domain.

As mentioned before, there is uncertainty in the number of evacuees in each pick-up point and only approximate values are available. Thus, Eq. (10) should be modified to include this uncertainty.

### 5.2. Fuzzy credibility theory for EVRP

To incorporate evacuation demand uncertainty, a triangular fuzzy variable \( \tilde{E} = (e_1, e_2, e_3) \) is considered as the number of evacuees at a given pick-up point. A disaster manager, planner or analyst studying such a problem can subjectively estimate, based on his experience, intuition and/or available historical data, that the analyst studying such a problem can subjectively estimate, based on his experience, intuition and/or available historical data, that the entering vehicle will eventually leave it. Eq. (9) is used for subtour elimination in VRP problem. Eq. (10) states the vehicle capacity constraint. In this equation, \( C - \sum_{i=1}^{m} e_i \) defines the available capacity and based on this constraint, this capacity should not be exceeded. Eq. (11) guarantees that each bus can be utilized at most once during the evacuation period. In other words, each vehicle has to do only one trip starts from a depot and ends at a shelter through the evacuation period. Eqs. (12) and (13) ensure that each pick-up point can be visited by one vehicle. That is, the number of evacuees in each pick-up point should not be split to be picked up by more than one vehicle. Eq. (14) describes the binary decision variable domain.

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According to basic definitions and formulations mentioned in 4.1, the possibility, necessity and credibility for this fuzzy variable \( \tilde{E} \) can be derived:

\[
\text{Pos}(\tilde{E} \geq r) = \begin{cases} 
1 & \text{if } r \leq e_2, \\
\frac{e_3 - r}{e_3 - e_2} & \text{if } e_2 \leq r \leq e_3, \\
0 & \text{if } r \geq e_3,
\end{cases}
\]

\[
\text{Nec}(\tilde{E} \geq r) = \begin{cases} 
1 & \text{if } r \leq e_1, \\
\frac{e_2 - r}{e_2 - e_1} & \text{if } e_1 \leq r \leq e_2, \\
0 & \text{if } r \geq e_2,
\end{cases}
\]

\[
\text{Cr}(\tilde{E} \geq r) = \begin{cases} 
1 & \text{if } r \leq e_1, \\
\frac{2e_2 - e_1 - r}{2(e_2 - e_1)} & \text{if } e_1 \leq r \leq e_2, \\
\frac{e_3 - r}{2(e_3 - e_2)} & \text{if } e_2 \leq r \leq e_3, \\
0 & \text{if } r \geq e_3.
\end{cases}
\]

Deciding to whether a vehicle is able to pick-up evacuees from the next pick-up point depends on its available capacity and the number of evacuees at that point. If vehicle's available capacity is equal to or greater than the number of evacuees of the next pick-up point, then it can drive to that pick-up point along its route and pick up more evacuees, otherwise it should depart to its closest shelter since it has not enough available capacity. When the number of evacuees is deterministic, it is easy to calculate whether the vehicle is able to drive to the next pick-up point or should depart to the shelter. However, when it is characterized by triangular fuzzy numbers, the decision making would be much more complex. The greater the difference between the available capacity and the number of evacuees at the next pick-up point, the greater the chance for vehicle to drive to that pick-up point.

The available capacity for vehicle \( k \) after visiting \( m \) pick-up points is represented in (18):

\[
Q_k^m = C - \sum_{i=1}^{m} e_i
\]

where \( C \) is the vehicle's initial capacity and \( e_i \) is the number of evacuees at pick-up point \( i \). Since \( e_i \) is a triangular fuzzy number, the \( Q_k^m \) is also a triangular fuzzy number and should be defined as (19):

\[
Q_k^m = \left( C - \sum_{i=1}^{m} e_{i1}, C - \sum_{i=1}^{m} e_{i2}, C - \sum_{i=1}^{m} e_{i3} \right) = (q_{1k}^m, q_{2k}^m, q_{3k}^m)
\]

According to (17) and (19), the credibility that picking up the evacuees at the next pick-up point does not exceed the available capacity of the vehicle is obtained by (20):

\[
Cr = Cr\{e_{m+1} \leq Q_k^m\} = 1 - Cr\{e_{m+1} \geq Q_k^m\} = 1 - Cr\{e_{m+1} - q_{3k}^m \geq 0\} = 1 - Cr\{e_{m+1} - q_{3k}^m \geq 0\} = \begin{cases} 
0 & \text{if } e_{m+1} \geq q_{3k}^m, \\
\frac{q_{2k}^m - q_{1k}^m}{2(q_{1k}^m - q_{2k}^m) - 2(q_{2k}^m - q_{3k}^m) - 2(q_{1k}^m - q_{3k}^m)} & \text{if } e_{m+1} \leq q_{3k}^m, e_{m+1} \geq q_{2k}^m, \\
\frac{q_{1k}^m - q_{2k}^m}{2(q_{2k}^m - q_{3k}^m) + 2(q_{1k}^m - q_{3k}^m)} & \text{if } e_{m+1} \leq q_{2k}^m, e_{m+1} \geq q_{1k}^m, \\
1 & \text{if } e_{m+1} \leq q_{1k}^m
\end{cases}
\]

Value of \( Cr \in [0, 1] \) indicates the measure of preference to send the vehicle to the next pick-up point. When \( Cr = 1 \), it means that vehicle should drive to the next pick-up point and when \( Cr = 0 \), it means that vehicle cannot cover the next pick-up point and should depart to the closest shelter.

To make a decision based on \( Cr \), a threshold index \( Cr^* \in [0, 1] \) is introduced. If \( Cr \geq Cr^* \), the vehicle drives to the next pick-up point, otherwise it departs to the closest shelter. Lower values of \( Cr^* \) express the tendency to use the vehicle capacity as much as possible. However, when \( Cr^* \) is low, there are more cases in which the vehicle arrives at the next pick-up point and is not able to pick up the planned evacuees due to its small available capacity. On the other hand, higher values of \( Cr^* \) reduces the probability of failures, while it increases the number of routes dramatically.

### 5.2.1. Optimization of \( Cr^* \) value

Evacuation routes are planned in advance using fuzzy number of evacuees. During evacuation operation, vehicles drive according to this plan and whenever they arrive at each pick-up point, they discover the actual number of evacuees. In the case when a vehicle cannot cover the pick-up point due to insufficient available capacity, it should depart to the closest shelter, disembark the boarded evacuees, return to the pick-up point when it had a failure and continue its planned route (Fig. 5).

As it is shown in Fig. 5(c), the vehicle has to travel additional time due to the failures and this additional travel time increases...
the total travel time. The value of \( C^* \) index greatly affects the number of failure cases and the additional time as well. Therefore, it should be determined in a way that results in a routing plan with the least total travel time.

In order to determine an optimum value for \( C^* \) index, EVRP is solved for each distinguished value of \( C^* \) index that vary in the interval of [0 1]. Then, the resulted routing plans should be evaluated. For this purpose, deterministic value of evacuees at each pick-up point is needed. However, we only have access to the triangular fuzzy numbers of evacuees. To overcome this deficiency, a stochastic simulation approach which is explained below is employed to simulate the deterministic number of evacuees at each pick-up point.

For each pick-up point \( i \), a random number \( d \) in the interval of triangular fuzzy number \([e_d, e_d, e_d] \) is generated and its fuzzy membership function \( \mu_{d_i} \) is calculated. Then, a random number \( r \) in the interval of [0,1] is generated. When \( r \leq \mu_{d_i} \), it is accepted that \( d \) is equal to the deterministic number of evacuees at pick-up point \( i \), otherwise evacuees at pick-up point \( i \) is not adopted as being equal to \( d \). In the latter, the generation of \( d \) and \( r \) continues until \( r \leq \mu_{d_i} \).

After simulating the deterministic number of evacuees, the additional travel time is calculated by moving along the planned routes, detecting the failures by accumulating the number of evacuees picked up at each point and comparing it with vehicle’s available capacity. Finally, the total travel time is determined for each \( C^* \) value.

The process of stochastic simulation and evaluation of the planned routes is repeated \( M \) times. Then, the average results are calculated for the corresponding \( C^* \) index.

5.3. Fuzzy-based genetic algorithm

VRP with fuzzy elements is a nondeterministic polynomial time-complete (NP-complete) problem i.e. it cannot be solved in polynomial time by any known way, so intelligent metaheuristics have gained wide applications in this area [28]. Similarly, EVRP includes fuzzy demands, so metaheuristics should be used to solve it in an efficient way.

GA is a well-known metaheuristic in routing problems and has been used successfully to solve VRP with fuzzy elements [18,48,5]. In this paper, a GA is designed which its contribution is in constructing solutions using fuzzy credibility theory. According to this, the fuzziness of evacuation demand and vehicle’s available capacity are taken into account and the algorithm assigns an order of pick-up points to the vehicle routes based on the \( C^* \) value.

The process of fuzzy-based GA is presented in Fig. 6 and its main elements in the context of EVRP are explained below.

5.3.1. Initialization

GA starts with four parameters: \( \text{GenMax} \), \( \text{PopSize} \), \( \text{Mrate} \) and \( \text{Crate} \). \( \text{GenMax} \) refers to the maximum number of generations the search proceeds, \( \text{PopSize} \) is the size of population, \( \text{Mrate} \) and \( \text{Crate} \) define the probability by which the solutions are mutated and
5.3.2. Solution representation

In this algorithm, each complete solution is coded by a sequence of numbers. Each number shows a pick-up point. Dummy zeros are inserted to indicate each distinct vehicle route. For example, Fig. 7(a) presents a solution with 4 vehicles and 10 pick-up points. Each vehicle route starts from depot and ends at the closest shelter.

Each solution is associated with a raw position representation (Fig. 7(b)). This representation does not include vehicle routes, each separated by a dummy zero. Raw position is provided for applying crossover and mutation operations which are discussed later in the paper.

5.3.3. Initial population

Initial population consists of PopSize number of solutions. Initially, each of these solutions is a random sequence of pick-up points in its raw position form.

5.3.4. Solution construction

Each raw position becomes a complete solution using SolutionConstruction() function. This function assigns pick-up points to the vehicle routes using fuzzy credibility theory. The procedure of this function on the raw position of one solution individual $S_{raw}$ is presented in Fig. 8. In this Figure, Vehicle($k$) includes an order of pick-up points assigned to the vehicle $k$. $L_k$, $Q_k$ and $E_i$ are triangular fuzzy numbers. $L_k$ is the fuzzy number of picked up evacuees by vehicle $k$, $Q_k$ represents the fuzzy available capacity of vehicle $k$ and $E_i$ is the fuzzy number of evacuees at pick-up point $i$.

5.3.5. Selection

Prior to the selection, the solutions in population should be evaluated based on their total travel time (fitness value) using Evaluation() function. To produce the new population, there are two steps:

1. Elitism: the solution with the minimum total travel time (the fittest solution) is selected as elite solution to be inserted directly into the new population for the next generation in order to preserve the population quality.

2. Roulette wheel selection: this selection strategy finds parents to generate off-springs (new solutions) for the next generation. This happens by assigning a part of a wheel to each solution individual which is in proportion to its fitness (total travel time). Fitter solutions are assigned a larger part and hence have a better chance of being selected for reproduction. The roulette wheel is spun for PopSize times. Each time Roulette Wheel stops, the solution corresponding to that part is selected.

5.3.6. Crossover

Crossover is implemented on the raw position of solutions (selected by roulette wheel) based on Crate. Uniform order crossover method is used for this purpose. In this method, first a random binary string with the same length of parents is generated. The first offspring solution preserves those pick-up points from parent 2 where the binary string is “1” in its position. The gaps in the offspring are also filled with elements from parent 1, but in the order of their appearance in parent 1. The second offspring solution is created using the same steps by switching parents. Fig. 9 provides an example for the uniform order crossover strategy.

5.3.7. Mutation

A two-point swap method is applied for mutation. Similar to the crossover, mutation is implemented on the raw position of solutions regarding the mutation rate. Two pick-up points are selected randomly from the solution and their positions are swapped (Fig. 10).
6. Case study

A case study is conducted over a 45 ha area of Tehran, the capital of Iran. 60 bus stops have been considered as evacuation pick-up points and six shelters have been determined at open spaces outside the affected area. There is also one equipped suburban public transportation terminal. It is assumed that this terminal can provide enough vehicles for evacuation operation. Fig. 11 shows the study area along with the location of depot, pick-up points and shelters. Historical travel time dataset, based on recurrent traffic congestion for the study area, was acquired from Tehran Municipality Transportation and Traffic Organization to be used as link travel times. The shortest travel time between the nodes (depot, pick-up points and shelters) are then calculated using Network Analysis tool box in the ArcGIS 10 software.

The number of evacuees at each pick-up point is a fuzzy number represented by \( E = (e_1, e_2, e_3) \). Managers or planners can determine \( e_1, e_2 \) and \( e_3 \) based on their experience or available historical data. To assist on this, the concept of Voronoi (Thiessen) diagram is used in this paper. Voronoi diagram involves with partitioning a given region into sub-areas based on some discrete generator points in a continuous space. The region of each partition consists of all points that are closer to the generator point than to any other ones [25].

7. Taguchi experimental design

The parameters of GA are optimized using the robust parameter setting approach proposed by Taguchi [36]. The Taguchi quality engineering method, employing design of experiments (DOE), is an important statistical tool that provides an efficient and systematic way to optimize designs for performance, quality, and cost [41].

In designing the algorithm parameters, the objective is to set the parameters in their optimized levels. Thus, the algorithm performance becomes robust against external factors. However, conducting a detailed study of parameters by trial and error is time consuming and costs heavily. Taguchi approach is a solution for this problem that decreases the number of experimental evaluations to a practical point and ensures achieving a near optimal parameter set. For this purpose, Taguchi approach utilizes simplified version of orthogonal arrays [37] came from DOE theory to study large number of parameters in small number of experimental evaluations. After the experiments were conducted, a signal-to-noise (S/N) ratio is provided as a measure of

Fig. 9. Uniform order crossover.

Fig. 10. Two-point swap mutation.

Fig. 11. Study area.
algorithm performance to analyze the results and select an appropriate parameter set. In the simplest form, the S/N ratio is the ratio of the mean (signal) to the standard deviation (noise). There are different types of standard S/N ratios, however, the S/N ratio is always interpreted in the same way: the larger the S/N ratio, the better [41]. The steps of the Taguchi parameter design implemented in Minitab software Version 16.2 are described below.

7.1. Selecting parameters and their suitable levels

The GA parameters include: Generation, Population, MutationRate and CrossoverRate which have significant impact on the algorithm’s robustness. According to the authors’ experience and similar problems in the literature, three levels for each of these parameters are determined (Table 1).

7.2. Selecting an appropriate orthogonal array

Total number of experiments is equal to \( L^P \) in which \( L \) and \( P \) equal to the number of levels and parameters, respectively. In this paper, the full factorial design requires \( 3^4 = 81 \) experiments to set the GA parameters which is not economical in terms of cost and time. So, Taguchi approach is followed to select the appropriate orthogonal array. According to [37], proper orthogonal array for our GA is \( L_9 \) in that nine combinations of parameters are considered (Table 2).

7.3. Carrying out the experiments

The experiments of Taguchi scheme \( L_9 \) presented in Table 2 are conducted on the case study. GA was coded in MATLAB R2014b on a DELL personal computer with a 2.66 GHz Intel processor and 4 GB RAM. Relative percentage deviation (RPD) is used to show the result of experiments. RPD is a mean that eliminates the influence...
of range on the results. The RPD of each instance is calculated as follows (21):

$$RPD_i = \frac{|TT_i - BestTT| \times 100}{|BestTT|}$$

(21)

where $i$ is the index of instance, $TT_i$ refers to the total travel time value resulted from instance $i$ and $BestTT$ presents the minimum total travel time value of all instances. It should be noticed that each of the experiment is replicated for three times and the average results for RPD are displayed in Table 3.

S/N ratios can be obtained from RPD values. Since the quality measure in this research is expected performance which prefers a "smaller is better" principle, the S/N ratio can be formulated as follows (22) [36]:

$$S/N ratio = -10 \log \left( \frac{\sum_{i=1}^{N} y_i^2}{N} \right)$$

(22)

where $i$ is the index of replicated instance, $N$ refers to the total number of replications for each instance (in this paper it is equal to three) and $y_i$ displays the RPD value of the replicated instance $i$.

The values of S/N ratios are shown in Table 3.

7.4. Analyzing the experiments

The mean of RPDs and S/N ratios for parameters in each level are depicted in Figs. 14 and 15, respectively. Considering the variation of S/N ratio and RPD in different levels for each parameter, it is clear that generation and population have greater effect on the algorithm performance compared to the other ones.

The less the RPD, the less the deviation from the best solution and the larger the S/N ratio, the better. Based on these, the optimal level of each factor is determined and presented in Table 4.
8. Results and discussion

The designed GA with optimum parameters is applied on the case study. The dispatcher preference index $Cr^*$ varies within the interval $[0, 1]$ by steps of length 0.05. For each value of $Cr^*$, GA is executed three times to obtain the planned total travel time and evacuation time. To evaluate the planned routes, the process of stochastic simulation and computation of additional travel time and final total travel time repeat $M=20$ times. The results are presented in Table 5 to illustrate and analyze the impact of $Cr^*$. Planned total travel time (PTTT) is determined using fuzzy number of evacuees, additional travel time (ATT) is calculated using deterministic number of evacuees obtained through stochastic simulation and final total travel time (FTTT) is equal to the PTTT plus ATT.

Fig. 16 represents PTTT, ATT and FTTT when dispatcher preference index $Cr^*$ varies. According to Table 5 and Fig. 16, PTTT rises generally as the value of $Cr^*$ increases, whereas ATT decreases. Lower values of $Cr^*$ are associated with higher ATT and lower PTTT. On the contrary, higher values of $Cr^*$ decreases ATT and increases PTTT. As shown in Fig. 16, when $Cr^*$ is less than 0.35, the

<table>
<thead>
<tr>
<th>$Cr^*$</th>
<th>Planned total travel time (Minute)</th>
<th>Additional travel time (Minute)</th>
<th>Final total travel time (Minute)</th>
<th>Planned evacuation time (Minute)</th>
<th>Final evacuation time (Minute)</th>
<th>Expected number of vehicles</th>
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</table>
The impact of uncertainty level on the planning evacuation time is also a significant factor in evacuation operation which is defined as the maximum required time for vehicles to totally evacuate the affected area. Planned evacuation time and final evacuation time are also displayed in Table 5. Planned evacuation time is obtained using fuzzy number of evacuees while final evacuation time is calculated using simulated deterministic number of evacuees. According to Table 5, evacuation time does not follow a particular trend with variation in $\text{Cr}^*$ and its minimum value is 19 min that happens when $\text{Cr}^*$ is 0.55 or more.

Expected number of vehicles increases as the value of $\text{Cr}^*$ grows. Lower values of $\text{Cr}^*$ demonstrates the planner tendency to utilize the vehicle’s capacity as much as possible and take risks by dispatching vehicles to pick-up points that may lead to failure. When $\text{Cr}^*$ = 0, one vehicle route is constructed and all the pick-up points are assigned to it in a least travel time manner. On the other hand, selecting higher values of $\text{Cr}^*$ is more reliable because it reduces the failure cases. When $\text{Cr}^*$ = 1, the number of vehicle routes is equal to the number of pick-up points. It means that each vehicle route consists of one pick-up point.

In order to select an appropriate $\text{Cr}^*$ index, a balance should be maintained among FTTT, final evacuation time and expected number of vehicles. It is clear that based on the total travel time, 0.35 is the most proper value for $\text{Cr}^*$ in which the FTTT reaches to its minimum value. On the other hand, evacuation time is minimized at $\text{Cr}^*$ = 0.55. However, FTTT and the expected number of vehicles reach to their maximum value at this point. Large total travel time means that the amount of fuel consumed by vehicles is high. Moreover, providing large number of vehicles is difficult and costly, particularly, when the number of pick-up points is large.

According to what was discussed above, $\text{Cr}^*$ = 0.35 is selected for this case study. At this point, expected number of vehicles is 32 which is a reasonable number (approximately half of the number of pick-up points), and finally, final evacuation time is in its third shortest value which is acceptable.

To analyze the impact of uncertainty on the final results, tests are implemented using four different uncertainty levels. To this end, $\varepsilon_2$ is considered as the original number of evacuees at each pick-up point. To define different levels, different uncertainty intervals are generated as triangular fuzzy numbers, ranging from 0.2 to 1.8 times the original number of evacuees ($\varepsilon_2$). For each single value of $\text{Cr}^*$, GA is executed for different levels and the results are shown in Table 6.

According to Table 6, as the uncertainty level decreases, PTTT is closer to FTTT. To better illustrate this fact, travel time trends for each level are demonstrated in Fig. 17. Clearly, as the uncertainty level increases FTTT deviates from PTTT. The same can be observed in the trends of planned evacuation time and final evacuation time displayed in Fig. 18. According to this Figure, as the uncertainty level decreases, the planned and final evacuation time get closer to each other.

What was described above is not astonishing, since when the uncertainty level is low, the fuzzy number (here is the number of evacuees) becomes sharp and can be interpreted as a crisp number. In this case, the solution obtained using a fuzzy-based approach is close to the deterministic solution.

The other point to mention is about credibility index. According to Table 6 and Fig. 17, the best value of $\text{Cr}^*$ based on the FTTT remains relatively fix with different uncertainty levels. It can be concluded that for this case study, the optimum value of $\text{Cr}^*$ is

\begin{table}[h]
\centering
\caption{The impact of uncertainty level on the final results.}
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline
$\text{Cr}^*$ & Level 1 & Level 2 & Level 3 & Level 4 \\
& (0.8,1.2) & (0.6,1.4) & (0.4,1.6) & (0.2,1.8) \\
\hline
\hline
$\text{PTTT}$ & $\text{ATT}$ & $\text{FTTT}$ & $\text{PTTT}$ & $\text{ATT}$ & $\text{FTTT}$ & $\text{PTTT}$ & $\text{ATT}$ & $\text{FTTT}$ & $\text{PTTT}$ & $\text{ATT}$ & $\text{FTTT}$ \\
\hline
0 & 0.151 & 433 & 584 & 0.271 & 491 & 762 & 0.351 & 470 & 821 & 0.268 & 478 & 746 \\
0.05 & 0.613 & 123 & 736 & 0.458 & 285 & 743 & 0.564 & 185 & 749 & 0.402 & 271 & 701 \\
0.1 & 0.651 & 101 & 752 & 0.489 & 237 & 726 & 0.570 & 166 & 736 & 0.450 & 271 & 673 \\
0.15 & 0.658 & 92 & 750 & 0.530 & 195 & 725 & 0.576 & 157 & 733 & 0.452 & 209 & 661 \\
0.2 & 0.667 & 86 & 753 & 0.546 & 179 & 725 & 0.593 & 129 & 722 & 0.509 & 153 & 662 \\
0.25 & 0.679 & 77 & 756 & 0.579 & 141 & 720 & 0.608 & 116 & 724 & 0.518 & 137 & 655 \\
0.3 & 0.696 & 57 & 755 & 0.628 & 98 & 726 & 0.627 & 93 & 720 & 0.520 & 127 & 647 \\
0.35 & 0.706 & 40 & 746 & 0.646 & 70 & 716 & 0.629 & 69 & 698 & 0.573 & 52 & 625 \\
0.4 & 0.718 & 36 & 754 & 0.677 & 24 & 701 & 0.690 & 68 & 758 & 0.648 & 50 & 698 \\
0.45 & 0.725 & 12 & 737 & 0.736 & 22 & 758 & 0.785 & 9 & 794 & 0.788 & 17 & 805 \\
0.5 & 0.756 & 12 & 768 & 0.772 & 11 & 783 & 0.822 & 0 & 822 & 0.841 & 0 & 841 \\
0.55 & 0.780 & 0 & 780 & 0 & 810 & 810 & 0 & 807 & 826 & 0 & 826 \\
0.6 & 0.783 & 0 & 783 & 0 & 811 & 811 & 0 & 811 & 830 & 0 & 830 \\
0.65 & 0.781 & 0 & 781 & 0 & 812 & 812 & 0 & 812 & 831 & 0 & 831 \\
0.7 & 0.781 & 0 & 781 & 0 & 813 & 813 & 0 & 813 & 833 & 0 & 833 \\
0.75 & 0.784 & 0 & 784 & 0 & 806 & 806 & 0 & 806 & 833 & 0 & 833 \\
0.8 & 0.782 & 0 & 782 & 0 & 813 & 813 & 0 & 813 & 837 & 0 & 837 \\
0.85 & 0.787 & 0 & 787 & 0 & 809 & 809 & 0 & 809 & 831 & 0 & 831 \\
0.9 & 0.783 & 0 & 783 & 0 & 809 & 809 & 0 & 809 & 834 & 0 & 834 \\
0.95 & 0.777 & 0 & 777 & 0 & 810 & 810 & 0 & 810 & 833 & 0 & 833 \\
1 & 0.781 & 0 & 781 & 0 & 810 & 810 & 0 & 810 & 834 & 0 & 834 \\
\hline
\end{tabular}
\end{table}
Fig. 17. The impact of uncertainty level on the total travel time (a) Level 1 (b) Level 2 (c) Level 3 (d) Level 4.

Fig. 18. The impact of uncertainty level on evacuation time (a) Level 1 (b) Level 2 (c) Level 3 (d) Level 4.
independent from uncertainty level. Hence, it can be determined once and used for several scenarios at different uncertainty levels.

9. Conclusion

Increasing occurrence of disasters and their consequences highlight the necessity of emergency planning prior to the event. Evacuation is an important activity for emergency management and is subjected to many sources of uncertainty. Thus, it is very improbable for evacuation to be implemented exactly as it is preplanned. In order to avoid serious difficulties during evacuation operation, one should consider uncertainties in the preplanning phase. One of the major uncertainties in evacuation is the demand uncertainty.

This paper optimized a public transit-based evacuation routing plan in urban areas. An EVRP was presented to model this plan. Based on this, evacuation vehicles depart from a depot, pick-up evacuees from predefined pick-up points (bus-stops) and transfer them to the closest shelter outside the affected area. Due to the uncertainty in evacuation demand, the number of evacuees at each pick-up point was considered as a fuzzy number. Then, a GA based on fuzzy credibility theory was designed to solve this evacuation problem with the objective of minimizing the total travel time. In order to analyze the impact of credibility preference index, CR, on the final results, a stochastic simulation was used to simulate the deterministic values of demands at each pick-up point.

The presented EVRP and designed algorithm were applied on a part of Tehran transportation network. Taguchi experimental design approach was used to set an optimum parameter combination for GA. For the considered case study, the best value for CR has been determined as 0.35, considering FTT, final evacuation time and expected number of vehicles. Furthermore, tests were implemented to analyze the influence of uncertainty level on final results. Based on the outcomes of these tests, the result obtained through fuzzy-based approach get closer to the deterministic result as the uncertainty level decreases. Moreover, it is discovered that best value of CR is independent of changes in the uncertainty level.

The proposed methodology can be implemented for different case studies during emergency planning phase. By introducing evacuation demand as fuzzy variable, it is easy to capture the uncertainty of this component in a real evacuation plan. Disaster managers can find the best estimate of CR to design the evacuation routes before the disaster occurrence and have a more reliable evacuation plan.

Acknowledgements

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