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A Fuzzy Gradient Chance-Constrained Evacuation Model for Managing Risks under Uncertain Climatic and Environmental Conditions

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ABSTRACT. Emergency evacuation is one of the most important risk management measures for nuclear accidents. Evacuation management systems contain various complexities, which have posed many challenges for decision makers. In the study, a fuzzy gradient chance-constrained evacuation model (FGCCEM) is proposed to address different uncertainties in evacuation management and planning. The FGCCEM is developed by incorporating fuzzy gradient chance-constrained programming into an inexact optimization framework. It is capable of balancing decision makers' optimism and pessimism, and can also reflect uncertainties expressed as discrete intervals. The proposed model is applied to a hypothetical case study of emergency evacuation planning for nuclear power plants. The results indicate that the FGCCEM can generate optimized evacuation schemes to maximize the total number of evacuees within limited time. Meanwhile, evacuation schemes with decision makers' varied perferences can be obtained through post-optimization analysis. The information obtained in this study can provide an insight into the complex relationships in evacuation management systems. It can also provide valuable decision support for effective risk management in response to nuclear emergencies.

Keywords: evacuation management, fuzzy gradient chance-constrained programming, optimization, uncertainty, nuclear power plants, risk management

1. Introduction

Emergency evacuation is an important measure for managing risks of nuclear power plants. Since the 1980's, simulation and optimization models for emergency evacuation management and planning have been widely investigated (Xie et al., 2010). Sheffi et al. (1982) developed a transportation network evacuation model for estimating network clearance time for areas surrounding nuclear power plant sites. Tweedie et al. (1986) proposed a methodology for estimating emergency evacuation times based on probabilistic mobilization time curves and pertinent evacuation network. Liu et al. (2006) introduced a two-level optimization framework for maximizing evacuation throughput and minimizing total evacuation time. After the 2011 Fukushima Daiichi nuclear disaster in Japan (Wada et al., 2012; Nomura et al., 2013), more efforts have been made to plan and optimize the management for a possible evacuation. Optimization models can help optimize resource allocation, maximize management efficiency, and directly answer the question "what should we do?" (Cai et al., 2008; Li et al., 2010; Li et al., 2013; Li et al., 2014). They have been recognized as an effective tool for emergency evacuation management in a stressful disaster environment. However, evacuation management systems are inherent with enormous uncertainties, such as imprecise estimates of radionuclide release duration, changing evacuation demands, and fuzzy information on road conditions and capacities (Caunhye et al., 2012). It is a major challenge to effectively reflect such uncertainties in the practical applications of emergency evacuation models (Malesic et al., 2015).

Quantifying system uncertainties is essential for risk analysis and management (Cheng et al., 2002; Lu et al., 2008; Fan et al., 2016a; Fan et al., 2016b). Previously, many optimization methods were developed for addressing various uncertainties and complexities in systems management problems (He, 2016; Li et al., 2016; Tong et al., 2016). Interval programming (IP) methods were developed to tackle uncertainties associated with the interval coefficients of optimization models (Huang and Cao, 2011). Chance-constrained programming (CCP) methods were proposed to deal with uncertainties in the format of probability distri butions (Li and Huang, 2009; Nematian, 2016). Meanwhile, possibility theory, which is considered as a mathematical counterpart of probability theory, was used for encoding the fuzzy information in decision-making processes (Yin et al., 1999; Li et al., 2008; Li et al., 2015). In fuzzy chance-constrained programming (FCCP) methods, possibilility was used to evaluate the satisfaction level of a fuzzy constraint, and thus quantify subjective information

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(Guo and Huang, 2009). More recently, the FCCP methods were further improved by introducing new measures to evaluate the violation/satisfaction of fuzzy constraints (Li et al., 2013; Soni and Joshi, 2015). For example, credibility was proposed as a measure of confidence level in a fuzzy environment and was used to reflect the fuzziness associated with parameters in solid waste management systems (Zhang and Huang, 2010). An m_λ-measure was introduced to generate optimal strategies for carbon capture, utilization and storage (Dai et al., 2014). These advanced FCCP methods can tackle fuzzy information in a more flexible and effective way (Liu et al., 2006; Li et al., 20 07; Guo and Huang, 2009). They have a great potential for applications in emergency management in terms of addressing the high degree of uncertainties that arise from the human aspects of emergency preparedness and response. However, there were very few studies on the application of these methods in the analysis and optimization of emergency evacua tion management systems.

Therefore, the objective of this study is to explore the possibilities of application of an advanced FCCP method in the field of emergency evacuation management. A fuzzy gradient chance-constrained programming (FGCCP) method will be introduced and incorporated into an inexact optimization framework. A fuzzy gradient chance-constrained evacuation model (FGCCEM) will then be developed to facilitate evacuation management for nuclear power plant accidents. The developed model will be able to address various uncertainties, in the formats of intervals and fuzzy sets. A hypothetical case study will be provided to demonstrate applicability of the developed model. The solutions will be analyzed and interpreted to provide optimized evacuation schemes. The information obtained in this study can provide an insight into the complex relationships in evacuation planning systems, as well as valuable decision support for effective risk management in response to nuclear emergencies.

2. Development of the Fuzzy Gradient Chance-Constrained Evacuation Model

2.1. Statement of Problem

Consider a problem in which an evacuation manager is responsible for making an evacuation plan in a nuclear emergency. Typically, there are two pre-designated emergency planning zone (EPZs) around each nuclear power plant: plume exposure pathway EPZ and ingestion exposure pathway EPZ (Figure 1). As implied by their names, the goal of protective actions during an emergency for the plume exposure pathway EPZ is to avoid or reduce dose from potential exposure of radioactive materials, while that for the ingestion exposure pathway EPZ is to avoid or reduce dose from potential ingestion of radioactive materials. General evacuation procedures for nuclear accidents are presented in Figure 2. If a nuclear accident occurs, the type and scale of the accident must be identified immediately. Subsequently, the maximum evacuation time can be estimated based on the release time of the radioactive substances. Residents in the plume exposure pathway EPZ must be sheltered or evacuated. They will first travel to a nearest assembly point (AP). Then, they will be transported from the assembly points to temporary shelters (TSs), where injured evacuees will be sent to nearby hospitals for further treatment and others will be transported to, and accommodated in, settlement cities/towns (SCTs). Meanwhile, residents in the ingestion exposure pathway EPZ will be asked to avoid consuming contaminated food and water and wait for further instructions.

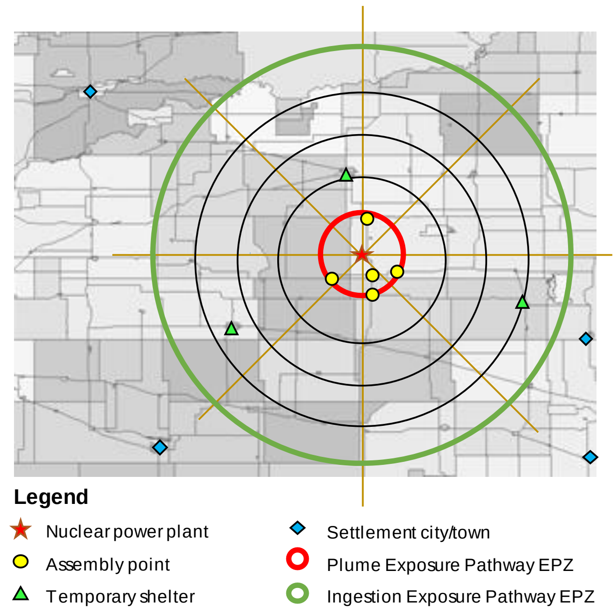

Figure 1. A typical nuclear EPZ map.

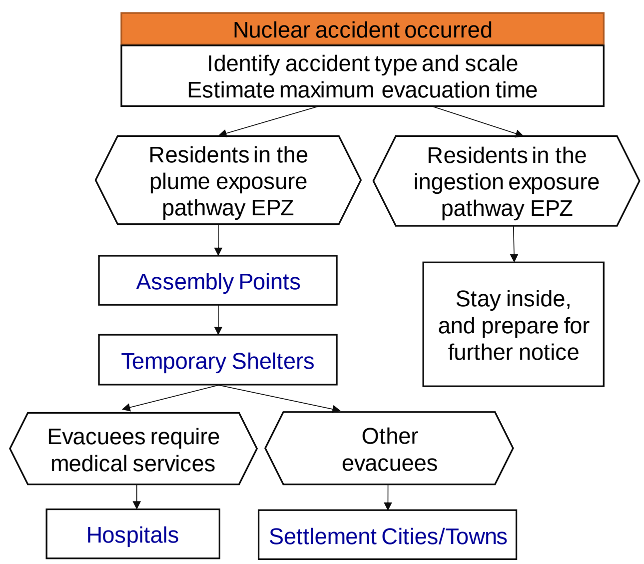

Figure 2. General evacuation procesdures.

In the event of a nuclear accident, the overarching objective of evacuation management is to evacuate as many residents as possible within a limited period of time. The problem can be formulated as maximizing the efficiency of evacuation, which is subjected to various factors, such as evacuation demands, transportation resources, and sheltering capacities at nearby locations. However, this problem is far beyond the capability of traditional optimization techniques, where coefficients and decision variables are deterministic values. In practice, evacuation problems could be significantly complicated by various uncertainties. For example, in a dynamic disaster environment, it could be extremely difficult to accurately estimate the evacuation demand (i.e., the total number of residents in the plume exposure pathway EPZ) and the sheltering capacities (i.e., the capacities of APs, TSs, SCTs, and hospitals). Furthermore, transportation capacities are affected by weather conditions and cost considerations, and thus should not be presented as deterministic values. How to effectively address such uncertainties and complexities and develop a reliable and robust optimization method for evacuation management is a major challenge facing the evacuation manager.

2.2. Fuzzy Gradient Chance-Constrained Programming

A common format of uncertainty in decision-making processes is subjective judgment. Subjective uncertainties can be quantified using the theory of fuzzy sets. Let $\tilde{b}$ be a fuzzy set of subjective interpretations. An optimization model with fuzzy constraints can be formulated as:

$$\text{Max } f = CX \tag{1a}$$

subject to:

$$AX \leq \tilde{b} \tag{1b}$$

$$X \geq 0 \tag{1c}$$

where f is the objective function, X is a vector of decision variables, and A and C are constant coefficients.

There are different forms of membership functions for fuzzy sets, such as triangular, trapezoidal, piecewise linear, and Gaussian (Pedrycz, 1994). In this study, the triangular membership function, which is the most common type of membership functions, is used for the purpose of demonstration. A triangular membership function for a fuzzy set $\tilde{b}$ on the universe of discourse T is defined as:

$$\mu(t) = \begin{cases} 0, \ if \ \ t < \underline{b} \\ \dfrac{t - \underline{b}}{b - \underline{b}}, \ if \ \ \underline{b} \leq t < b \\ 1, \ if \ \ t = b \\ \dfrac{t - \bar{b}}{b - \bar{b}}, \ if \ \ b < t \leq \bar{b} \\ 0, \ if \ \ t > \bar{b} \end{cases} \tag{2}$$

where $\underline{b}$, $\bar{b}$, and b are the minimum, maximum, and most-likely values of $\tilde{b}$, respectively.

In traditional FCCP methods, possibility is often used to describe the likelihood of a fuzzy event occurring (Li et al., 2013). The possibility of the fuzzy event $AX \leq \tilde{b}$ is defined as follows:

$$Pos(AX \leq \tilde{b}) = \begin{cases} 1, \ if \ \ AX \leq b \\ \dfrac{AX - \bar{b}}{b - \bar{b}}, \ if \ \ b \leq AX \leq \bar{b} \\ 0, \ if \ \ AX \geq \bar{b} \end{cases} \tag{3}$$

Possibility is an adventurous measure that only reflects decision makers' optimistic interpretation. To better balance decision makers' optimism and pessimism, an advanced measure named fuzzy gradient measure (FGM), was proposed (Xu et al., submitted in 2016). The FGM is defined as follows:

$$\text{FGM}(AX \leq \tilde{b}) = \lambda \text{P}os(AX \leq \tilde{b}) + \left(1 - \lambda\right) Nec(AX \leq \tilde{b}) \tag{4}$$

where $Nec(\cdot)$ is the necessity of the fuzzy event $AX \leq \tilde{b}$ and λ is a gradient value to balance the weights of possibility and necessity. With the minimum, maximum and most-likely values of $\tilde{b}$, the FGM can be calculated as follows:

$$\text{FGM}(AX \leq \tilde{b}) = \begin{cases} 1, \ if \ \ AX \leq \underline{b} \\ \dfrac{b - \lambda \underline{b} - AX(1 - \lambda)}{b - \underline{b}}, \ if \ \ \underline{b} \leq AX \leq b \\ \dfrac{\lambda(\bar{b} - AX)}{\bar{b} - b}, \ if \ \ b \leq AX \leq \bar{b} \\ 0, \ if \ \ AX \geq \bar{b} \end{cases} \tag{5}$$

Then, a threshold value α can be introduced to evaluate the satisfaction level of the fuzzy constraint $AX \leq \tilde{b}$, and the fuzzy constraint can be converted to a deterministic piecewise constraint as follows:

$$\text{FGM}(AX \leq \tilde{b}) \geq \alpha \tag{6}$$

In emergency management, more often than not, decision makers tend to be conservative in terms of violating system constraints. Thus, a conservative FGM scenario where $AX \leq b$ is recommended, and Equation (6) can be rewritten as:

$$\frac{b - \lambda \underline{b} - AX(1 - \lambda)}{b - \underline{b}} \geq \alpha \tag{7}$$

Therefore, a fuzzy gradient chance-constrained programming (FGCCP) model can be obtained as follows:

$$\text{Max } f = CX \tag{8a}$$

subject to:

$$AX \leq \frac{b - \lambda \underline{b} - \alpha(b - \underline{b})}{(1-\lambda)} \tag{8b}$$

$$X \geq 0 \tag{8c}$$

$$0 \leq \lambda \leq 1 \tag{8d}$$

When uncertainties associated with model parameters A and C are given as intervals, the FGCCP model can be reformulated as follows:

$$\text{Max } f^{\pm} = C^{\pm} X^{\pm} \tag{9a}$$

subject to:

$$A^{\pm} X^{\pm} \leq \frac{b - \lambda \underline{b} - \alpha^{\pm}(b - \underline{b})}{(1-\lambda)} \tag{9b}$$

$$X^{\pm} \geq 0 \tag{9c}$$

$$0 \leq \lambda \leq 1 \tag{9d}$$

2.3. Emergency Evacuation Management under Uncertainty

The following hypothetical problem can be used to illustrate the FGCCP approach. An evacuation manager is asked to make an evacuation plan in a nuclear emergency. After identifying the reactor that failed, it is determined that a complete evacuation of the plume exposure pathway EPZ must be accomplished within six hours. The total number of residents in the plume exposure pathway EPZ is an inexact number, given as [21,000, 23,000]. There are five pre-designated APs (i = 1, 2, …, 5), three TSs (j = 1, 2, 3), and four SCTs (k = 1, 2, …, 4) to serve the emergency evacuation demands (Figure 1). The APs have no capacity constraints, as they are only temporary waiting locations for residents to be dispatched to the ultimate SCTs. Residents in the plume exposure pathway EPZ make their own arrangements to move to the APs. Residents in the ingestion exposure pathway EPZ are suggested to stay inside and wait for further instructions. However, in the stressful disaster environment, it is expected that some residents in the ingestion exposure pathway EPZ will travel to the APs or TSs and require to be evacuated, which is considered beyond the evacuation manager's control. The capacities of the three TSs are [300, 400], [200, 300], and [250, 400], respectively. Severely injured residents and residents with medical conditions will be evacuated by ambulances, and will be transported to hosipitals in the SCTs, where medical services will be provided. The evacuation time is divided into six 1-hour periods (t = 1, 2, …, 6). The proportions of residents who require medical evacuation chan- ge with time, and are 1, 1, 2, 2, 1, and 0.5 percent for t = 1, 2, …, 6, respectively.

Transportation capacities of the paths between APs, TSs, and SCTs are estimated in the prioritization of evacuation efforts. The maximum community-level evacuation rates from APs to TSs are limited by modes of transportation available and/or preferred by evacuees, as well as distances to the host TSs. It is not practical to accurately estimate the maximum community-level evacuation rates; however, the uncertainties can be described as intervals (Table 1). Limitations to modes of transportation (e.g. the total number of available buses, road conditions, and/or characteristics of the available aerodrome) and weather conditions (e.g. precipitation, and wind speed and direction) are significant factors in determining the maximum evacuation flow rates from TSs to SCTs. Fuzzy estimates of the maximum evacuation flows are provided in Figure 3. The estimates are based on available transportation resources as well as locations of the TSs to SCTs; meanwhile, the λ value in the FGCCP approach allows the evacuation manager to make his/her adjustments under different environmental conditions.

Table 1. The Maximum Evacuation Flow from APs to TSs (Person/Hour)

	TS 1	TS 2	TS 3
AP 1	[210, 340]	[260, 440]	[210, 350]
AP 2	[210, 340]	[260, 440]	[530, 790]
AP 3	[210, 340]	[170, 260]	[210, 350]
AP 4	[210, 340]	[170, 260]	[210, 360]
AP 5	[210, 340]	[260, 440]	[530, 790]

Based on Model (9), the fuzzy gradient chance-constrained evacuation model (FGCCEM) can be formulated. The objective is to maximize the total number of evacuees from the TSs to the SCTs within six hours:

$$\text{Max } f^{\pm} = \sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{t=1}^{6} x_{ijt}^{\pm} \tag{10a}$$

where $x_{ijt}^{\pm}$ is the evacuee flow from AP i to TS j in the t^{th} period.

The optimization problem is subject to a number of constraints:

(1) Firstly and most importantly, the plume exposure pathway EPZ must be evacuated within the limited time:

$$\sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{t=1}^{6} x_{ijt}^{\pm} \geq PEPZ^{\pm} \tag{10b}$$

where $x_{ijt}^{\pm}$ is the evacuee flow from AP i to TS j in the t^{th} period, and $PEPZ^{\pm}$ is the total number of residents in the plume exposure pathway EPZ.

(2) Residents who require specialized medical services or treatment for radiation injury must be transferred to hospitals in the SCTs:

$$\sum_{k=1}^{4} z_{jkt}^{\pm} \ge \gamma_t \sum_{i=1}^{5} x_{ijt}^{\pm}, \ \forall j, \ t \tag{10c}$$

where $z_{jkt}^{\pm}$ is the flow of evacuees transported by ambulances from TS j to SCT k in the t^{th} period, and γ_t is the percentage of residents who require medical evacuation in the t^{th} period.

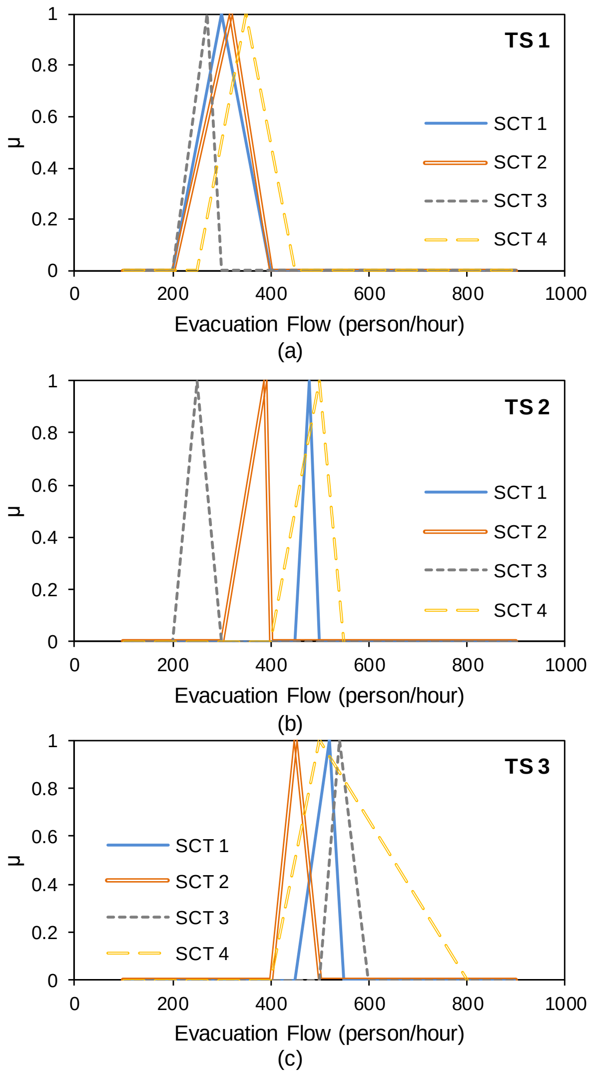

Figure 3. The maximum evacuation flows from TS 1 (a), TS 2 (b), and TS 3 (c) to the four SCTs.

(3) The evacuation rates from APs to TSs and from TSs to SCTs are subject to the local transportation capacities:

$$x_{ijt}^{\pm} \le ATT_{ij}^{\pm}, \ \forall i, \ j, \ t \tag{10d}$$

$$y_{jkt}^{\pm} \le TTS_{jk}, \ \forall j, \ k, \ t \tag{10e}$$

where $ATT_{ij}^{\pm}$ is the maximum evacuee flow from AP i to TS j, $y_{jkt}^{\pm}$ is the evacuee flow from TS j to SCT k in the t^{th} period, and TTS_{jk} is the maximum evacuee flow from TS j to SCT k.

(4) Medical evacuation is subject the total number of available ambulances:

$$\sum_{k=1}^{4} z_{jkt}^{\pm} \le MTTS_j^{\pm}, \ \forall j, \ t \tag{10f}$$

where $MTTS_j^{\pm}$ is the number of available ambulances at TS j.

(5) The number of evacuees that can be accommodated at each TS is subject to its sheltering capacity:

$$\sum_{t=1}^{n}\sum_{i=1}^{5} x_{ijt}^{\pm} - \sum_{t=1}^{n}\sum_{k=1}^{4} y_{jkt}^{\pm} - \sum_{t=1}^{n}\sum_{k=1}^{4} z_{jkt}^{\pm} \le TSC_j^{\pm}, \ \forall j, \ n = 1,2,...,6 \tag{10g}$$

where $TSC_j^{\pm}$ is the maximum number of evacuees that can be accommodated at TS j.

(6) There are a set of non-negativity and integer constraints (Huang et al., 2016):

$$x_{ijt}^{\pm} \ge 0, \text{ and } x_{ijt}^{\pm} \in N, \ \forall i, \ j, \ t \tag{10h}$$

$$y_{jkt}^{\pm} \ge 0, \text{ and } y_{jkt}^{\pm} \in N, \ \forall j, \ k, \ t \tag{10i}$$

$$z_{jkt}^{\pm} \ge 0, \text{ and } z_{jkt}^{\pm} \in N, \ \forall j, \ k, \ t \tag{10j}$$

Model (10) can be solved through an interactive two-step algorithm developed by Huang and Fan (2012). Using the FGCCP method, a conservative submodel, which corresponds to the lower bound of the objective function f^-, can be first established as follows:

$$\text{Max } f^- = \sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{t=1}^{6} x_{ijt}^{-} \tag{11a}$$

subject to:

$$\sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{t=1}^{6} x_{ijt}^{-} \ge PEPZ^{+} \tag{11b}$$

$$\sum_{k=1}^{4} z_{jkt}^{-} \ge \gamma_t \sum_{i=1}^{5} x_{ijt}^{-}, \ \forall j, \ t \tag{11c}$$

$$x_{ijt}^{-} \le ATT_{ij}^{-}, \ \forall i, \ j, \ t \tag{11d}$$

$$\text{FGM}(y_{jkt}^{-} \le TTS_{jk}) > \alpha^{+}, \ \forall j, \ k, \ t \tag{11e}$$

$$\sum_{k=1}^{4} z_{jkt}^{-} \le MTTS_j^{-},\ \forall j,\ t \tag{11f}$$

$$\sum_{t=1}^{n}\sum_{i=1}^{5} x_{ijt}^{-} - \sum_{t=1}^{n}\sum_{k=1}^{4} y_{jkt}^{-} - \sum_{t=1}^{n}\sum_{k=1}^{4} z_{jkt}^{-} \le TSC_j^{+},\ \forall j,\ n = 1,2,...,6 \tag{11g}$$

$$x_{ijt}^{-} \ge 0, \text{ and } x_{ijt}^{-} \in N,\ \forall i,\ j,\ t \tag{11h}$$

$$y_{jkt}^{-} \ge 0, \text{ and } y_{jkt}^{-} \in N,\ \forall j,\ k,\ t \tag{11i}$$

$$z_{jkt}^{-} \ge 0, \text{ and } z_{jkt}^{-} \in N,\ \forall j,\ k,\ t \tag{11j}$$

Let $x_{ijt\_opt}^{-}$, $y_{jkt\_opt}^{-}$, and $z_{jkt\_opt}^{-}$ be the solutions of Submodel (11). Then, an optimistic submodel, which corresponds to the upper bound of the objective function f^{+}, can be established as follows:

$$\text{Max } f^{+} = \sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{t=1}^{6} x_{ijt}^{+} \tag{12a}$$

subject to:

$$\sum_{i=1}^{5}\sum_{j=1}^{3}\sum_{t=1}^{6} x_{ijt}^{+} \ge PEPZ^{-} \tag{12b}$$

$$\sum_{k=1}^{4} z_{jkt}^{+} \ge \gamma_t \sum_{i=1}^{5} x_{ijt}^{+},\ \forall j,\ t \tag{12c}$$

$$x_{ijt}^{+} \le ATT_{ij}^{+},\ \forall i,\ j,\ t \tag{12d}$$

$$\text{FGM}(y_{jkt}^{+} \le TTS_{jk}) > \alpha^{-},\ \forall j,\ k,\ t \tag{12e}$$

$$\sum_{k=1}^{4} z_{jkt}^{+} \le MTTS_j^{+},\ \forall j,\ t \tag{12f}$$

$$\sum_{t=1}^{n}\sum_{i=1}^{5} x_{ijt}^{+} - \sum_{t=1}^{n}\sum_{k=1}^{4} y_{jkt}^{+} - \sum_{t=1}^{n}\sum_{k=1}^{4} z_{jkt}^{+} \le TSC_j^{-},\ \forall j,\ n = 1,2,...,6 \tag{12g}$$

$$x_{ijt}^{+} \ge x_{ijt\_opt}^{-}, \text{ and } x_{ijt}^{+} \in N,\ \forall i,\ j,\ t \tag{12h}$$

$$y_{jkt}^{+} \ge y_{jkt\_opt}^{-} \text{ and } y_{jkt}^{+} \in N,\ \forall j,\ k,\ t \tag{12i}$$

$$z_{jkt}^{+} \ge z_{jkt\_opt}^{-}, \text{ and } z_{jkt}^{+} \in N,\ \forall j,\ k,\ t \tag{12j}$$

By solving the deterministic Submodel (12), solutions $x_{ijt\_opt}^{+}$, $y_{jkt\_opt}^{+}$, and $z_{jkt\_opt}^{+}$ can be generated. Thus, the solutions of Model (10) can be obtained as follows:

$$f_{opt}^{\pm} = [f_{opt}^{-},\ f_{opt}^{+}] \tag{13}$$

$$x_{ijt\_opt}^{\pm} = [x_{ijt\_opt}^{-},\ x_{ijt\_opt}^{+}] \tag{14}$$

$$y_{jkt\_opt}^{\pm} = [y_{jkt\_opt}^{-},\ \mathrm{y}_{jkt\_opt}^{+}] \tag{15}$$

$$z_{jkt\_opt}^{\pm} = [z_{jkt\_opt}^{-},\ \mathrm{z}_{jkt\_opt}^{+}] \tag{16}$$

3. Results and Discussion

3.1. Baseline Scenario

The developed FGCCEM was solved using the aforementioned two-step algorithm under a baseline scenario where λ=0.5. The λ value indicates the evacuation manager's neutral preferences regarding evacuation efficiency. The satisfaction level of fuzzy constraints was defined as [0.6, 0.9]. The solutions of most decision variables are intervals, which demonstrates that the related decisions are sensitive to the uncertain model inputs (Huang et al., 1996). The solutions provide an optimized evacuation scheme, where the optimal number of evacuees carried by each route (from AP *i* to TS *j*, and from TS *j* to SCT *k*) during each period is given as an interval. A total of [23,160, 31,780] residents would be evacuated from the APs. A complete evacuation of the plume exposure pathway EPZ would be accomplished within six hours. In addition, [2,160, 8,780] residents in the the ingestion exposure pathway EPZ would also be evacuated.

The optimized dynamic flows from APs to TSs are shown in Figure 4. During the six hours, AP 2 would be the busiest AP, handling [6,000, 8,843] evacuees. TS 3 would house [10,140, 13,275] evacuees in total, which makes it the busiest shelter during the evacuation process. Among the 15 routes between APs and TSs, AP 2 to TS 3 is the one with the most traffic, carrying a total of [3,180, 4,553] evacuees. Among the five APs, AP 3 would handle the least evacuees (i.e., [3,540, 4,680]), and its evacuee flow to TSs 2 and 3 would be the lowest ([1,020, 1,560] and [1,260, 1,470], respectively). TS 1 is expected to house a total of [6,300, 8,210], which is the lowest among the three TSs.

It is worth mentioning that although TS 3 is expected to handle the most evacuees, it is not the largest TS among the three. The capacities of TSs 1 and 3 are very close: [300, 400] and [250, 400], respectively. However, the total number of evacuees handled by TS 1 would be the lowest, which is approximately 38% lower than that of TS 3. Moreover, although the routes from AP 2 to TS 3 and TS 5 both have the highest maximum traffic capacity of [530, 790] person/hour, the number of evacuees carried by the two routes would be slightly different: [3,180, 4,553] and [3,180, 3,700] for AP 2 to TSs 2 and 3, respectively. Similar results can be obtained through the analysis of the least busy facilities. The AP, TS, or route with the lowest capacity would not necessarily carry the least evacuees. This implies that evacuation management decisions should not be made based on capacity factors only. Evacuation management systems are complex systems with various components. There are complex relationships and dynamic interactions between different system components. To obtain an optimized evacuation scheme, a system approach should be adopted. The developed FGCCEM can help tackle the interconnected complexities and inherent uncertainties, and thus analyze the evacuation problem in a holistic and effective way.

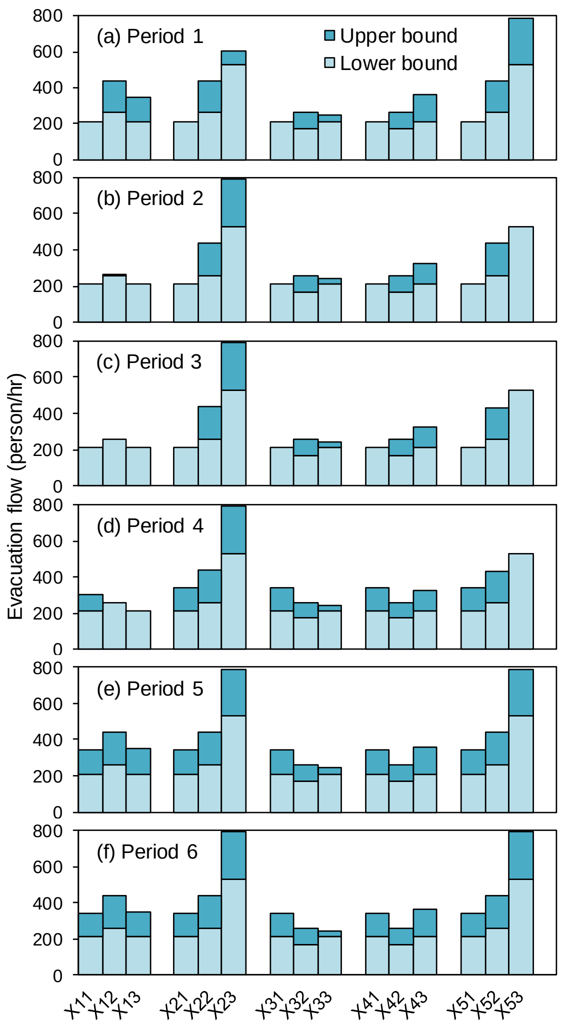

Figure 4. Evacuation flow (x_{ij}) from AP i to TS j during the six periods.

The evacuation flow from the three TSs to the four SCTs are presented in Figure 5. SCTs 1 to 4 would host [6,840, 7,440], [5,712, 6,492], [5,592, 6,072], and [3,488, 7,680] evacuees, respectively. The most and least demanding routes both lead to SCT 3. The path from TS 3 would the most demanding, carrying [3,048, 3,168] evacuees, while the one from TS 2 would be the least demanding, handling [1,260, 1,410] evacuees. The most hectic time would be period 1, with [4,134, 4,686] evacuees being transferred to SCTs. This is because the TSs are at their full capacity and could accommodate the most evacuees at the beginning of the evacuation process. As the TSs receive more evacuees, the number would gradually decrease to [3,294, 4,254] towards the end of the evacuation.

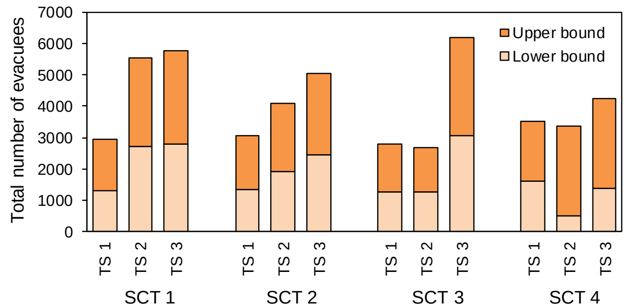

Figure 5. Evacuation flow from TSs to SCTs.

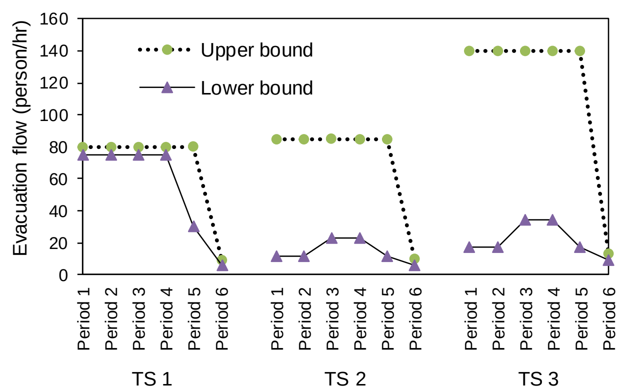

Figure 6. Medical evacuation scheme for each TS.

The medical evacuation scheme was also optimized and generated from the FGCCEM (Figure 6). The total numbers of evacuees who require medical transfer would be [104, 305], [104, 305], [132, 305], [132, 305], [59, 305], and [21, 32] during periods 1 to 6, respectively. It is obvious that the lower bound of medical transportation demand varies with time significantly, while the upper bound does not. This indicates that the availability of medical transportation resources would not be a limiting factor when the system approaches their upper bounds. It should be noted that the ranges of the solution intervals are relatively large, particularly for TSs 2 and 3 during periods 1 to 5. This implies there are significant uncertainties associated with the medical evacuation scheme. It is suggested more information, such as medical staff, facilities, and back-ups in each SCT, be collected and integrated in the model. This could help narrow the solution intervals, provide more precise decision support, and thus mitigate the risk of ineffective medical evacuation.

3.2. Analysis of Fuzzy Constraints

One of FGCCEM's advantages is its ability to reflect decision makers' optimistic or pessimistic preferences on uncertain constraints. In the FGCCEM, fuzzy constraints are pre-defined based on experts' estimation. During the implementation process, they can also be further adjusted by decision makers using different fuzzy gradient (λ) values. For example, the transportation capacity constraints can be pre-defined by transportation experts based on the availability and accessibility of transportation resources. When a nuclear accident occurs, the on-site evacuation manager can further make an optimistic, neutral, or pessimistic judgement to adjust these constraints according to realistic environmental conditions, such as weather conditions and/or the evacuees' level of co-operation/preparedness.

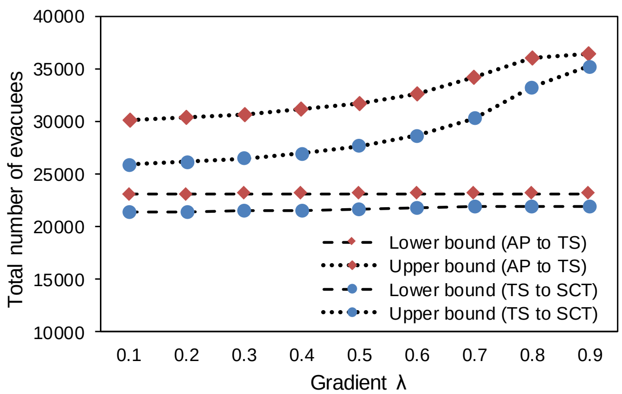

Figure 7. Change in the total number of evacuees under different scenarios.

In addition to the baseline evacuation scheme (λ = 0.5), solutions under eight more scenarios with different λ values were also obtained. Scenarios with λ = 0.1, 0.2, …, 0.9 are denoted as S1, S2, …, S9, respectively. The λ values of 0.1 to 0.9 represent the evacuation manager's "practically pessimistic", "almost pessimistic'', "very pessimistic'', "quite pessimistic'', "neutral", "quite optimistic", "very optimistic", "almost optimistic", and "practically optimistic" preferences regarding the transportation constraints for routes between TSs and SCTs, respectively. The change in total number of evacuees under different scenarios are presented in Figure 7. If λ increases from 0.1 to 0.9, the total number of residents evacuated from APs to TSs would increase from [23,062, 30,125] to [23,160, 36,450], and that from TSs to SCTs would increase from [21,416, 25,889] to [21,943, 35,269]. Changes in the lower bound solutions are much less significant compared to those in the upper bound solutions. This implies that the flow capacity constraints of routes between TSs and SCTs are more important when the actual system conditions are close to the upper-bound model status.

The change in number of evacuees handled by each AP under different scenarios were also calculated. As changes in the lower-bound solutions are relatively insignificant, only upper-bound solutions are presented in Figure 8. In the upper-bound model, the numbers of evacuees handled at APs 1 to 5 would increase by 1,836, 1,180, 590, 951, and 1,768, respectively. APs 3 and 4 are the only two APs where the number of evacuees would increase constantly as the flow constraint is being released. For the other three APs, as the λ value increase, small fluctuations in the number of evacuees are expected. This indicates that there would be a re-allocation of evacuation flow within the system every time the route capacity constraint changes.

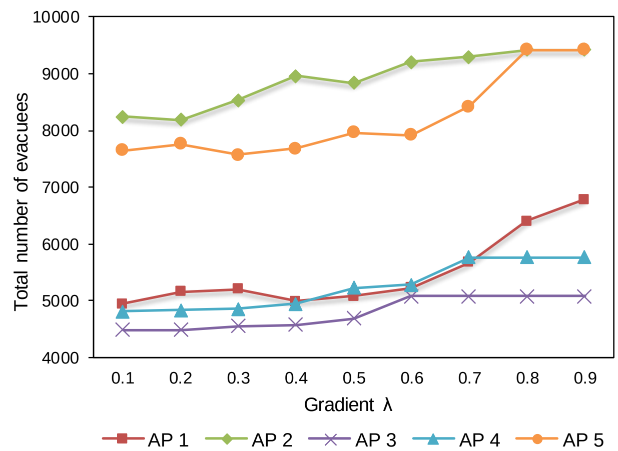

Figure 8. Change in the number of evacuees handled by each AP under different scenarios (upper-bound solutions).

The lower and upper bounds of total evacuees transferred to the three TSs during each period under the nine scenarios are shown in Figure 9. The average numbers of evacuees of the nine scenarios are [4,143, 5,045], [3,819, 4,941], [3,678, 4,916], [3,448, 4,832], [3,316, 4,751], and [3,274, 4,492] during periods 1 to 6, respectively. In the lower-bound solutions, there is a decreasing trend in the total number of evacuees from periods 1 to 6. The decreasing trend with time is not as significant in the upper-bound solutions. When the decision maker's preferences change from "practically pessimistic" (λ = 0.1) to "quite optimistic" (λ = 0.6), the total number of evacuees would increase gradually. However, when his/her preferences change from "very optimistic" (λ = 0.7) to "practically optimistic" (λ = 0.9), the changes in the total number of evacuees would be much more significant. In the lower-bound model, the gradual increasing trend is expected during periods 4 and 5. The numbers of evacuees in periods 1 and 6 would slightly decrease and then increase, while the number during period 3 would decrease gradually. The number of evacuees during period 2 would first increase when λ = 0.8, and then return to the λ = 0.7 level when λ = 0.9. Similarly, the changes in the upper-bound model when λ increases from 0.7 to 0.9 are significant, with no noticeable pattern. The results show that the decision maker's preferences would significantly affect the design of the evacuation scheme. This is particularly true when the decision maker becomes more optimistic. The FGCCEM can effective evacuation scheme. This is particularly true when the decision maker becomes more

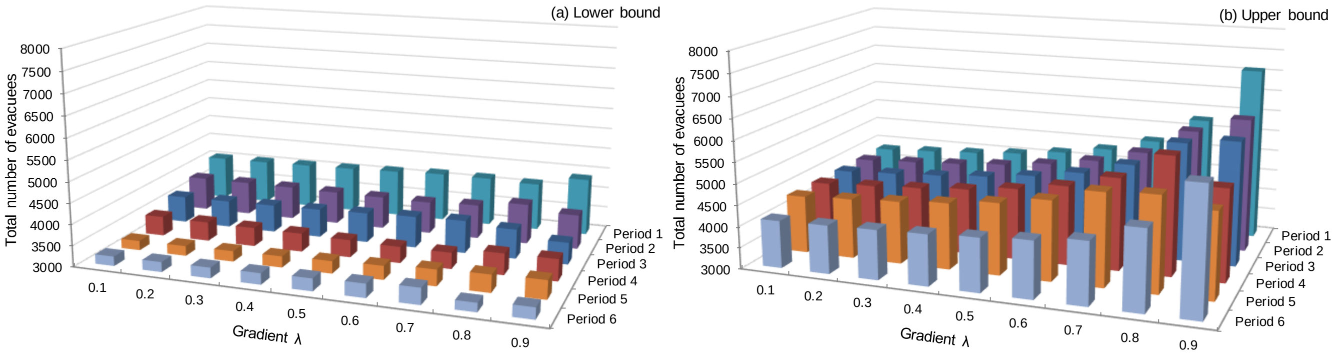

Figure 9. Total number of evacuees transferred from TSs in each period under different scenarios.

optimistic. The FGCCEM can effective incorporate the evacuation manager's on-site judgement into the decision-making process, and thus provide more robust decision support for risk management under various uncertainties.

4. Conclusions

In this study, a fuzzy gradient chance-constrained evacuation model (FGCCEM) was developed for managing risks of nuclear power plants under uncertainty. In nuclear evacuation management, decision makers' subjective judgement can be interpreted as fuzzy information, which can be incorporated into the evacuation optimization process as fuzzy constraints. A fuzzy gradient chance-constrained programming (FGCCP) method was introduced to convert fuzzy constraints to a deterministic constraints and generate quantifiable results. In the FGCCP method, the fuzzy gradient was used as a dual measure based on necessity and possibility for evaluating the satisfaction level of fuzzy constraints and reflecting decision makers' optimistic or pessimistic preferences. The FGCCP method was further incorporated into an inexact optimization framework, in order to tackle multiple uncertainties in the formats of fuzzy sets and intervals.

A hypothetical case study was used to demonstrate the applicability of the FGCCEM. Stable interval solutions were obtained by solving the FGCCEM through an interactive two-step algorithm. The solutions were further interpreted for generating an optimal evacuation plan for the hypothetical nuclear disaster. The results demonstrated that the proposed FGCCEM can help obtain a better understanding of the evacuation management system and reflect the interconnected complexities and various uncertainties. Due to the complexity of the evacuation systems and the multitude of factors influencing the decision-making processes, optimization approaches are important for the analysis and planning of emergency evacuations. The FGCCEM can help mitigate the adverse influence of nuclear accidents and enhance the capability of risk management. It can also help decision makers make adjustments on system constraints more effectively to cope with a dynamic and uncertain disaster environment. This model could be advanced by introducing other advanced optimization methods, such as multi-objective programming and multi-stage stochastic programming, to tackle more uncertainties and complexities in the future.

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References

Cai, Y.P., Huang, G.H., Yang, Z.F., Lin, Q.G., Bass, B., and Tan, Q. (2008). Development of an optimization model for energy systems planning in the Region of Waterloo. *Int. J. Energy Res.*, 32(11), 988-1005. https://dx.doi.org/10.1002/er.1407

Caunhye, A.M., Nie, X., and Pokharel, S. (2012). Optimization models in emergency logistics: A literature review. *Socio Econ. Plan Sci.*, 46(1), 4-13. https://dx.doi.org/10.1016/j.seps.2011.04.004

Cheng, S., Chan, C.W., and Huang, G.H. (2002). Using multiple criteria decision analysis for supporting decisions of solid waste management. *J. Environ. Sci. Health. A*, 37(6), 975-990. https://dx.doi.org/10.1081/ESE-120004517

Dai, C., Cai, Y., Li, Y., Sun, W., Wang, X., and Guo, H. (2014). Optimal strategies for carbon capture, utilization and storage based on an inexact m λ-measure fuzzy chance-constrained programming. *Energy*, 78, 465-478. https://dx.doi.org/10.1016/j.energy.2014.10.034

Fan, Y., Huang, W., Huang, G., Huang, K., Li, Y., and Kong, X. (2016a). Bivariate hydrologic risk analysis based on a coupled entropy-copula method for the Xiangxi River in the Three Gorges Reservoir area, China. *Theor. Appl. Climatol.*, 125(1-2), 381-397. https://dx.doi.org/10.1007/s00704-015-1505-z

Fan, Y., Huang, W., Huang, G., Li, Y., Huang, K., and Li, Z. (2016b). Hydrologic risk analysis in the Yangtze River basin through coupling Gaussian mixtures into copulas. *Adv. Water Resour.*, 88, 170-185. https://dx.doi.org/10.1016/j.advwatres.2015.12.017

Guo, P., and Huang, G.H. (2009). Two-stage fuzzy chance-constrained programming: application to water resources management under dual uncertainties. *Stochastic Environ. Res. Risk Assess.*, 23(3), 349-359. https://dx.doi.org/10.1007/s00477-008-0221-y

He, J. (2016). Probabilistic evaluation of causal relationship between variables for water quality management. *J. Environ. Inf.*, 28(2), 110-119. https://dx.doi.org/10.3808/jei.201600353

Huang, G., and Cao, M. (2011). Analysis of solution methods for interval linear programming. *J. Environ. Inf.*, 17(2), 54-64. Ht-tps://dx.doi.org/10.3808/jei.201100187

Huang, G., Cohen, S., Yin, Y., and Bass, B. (1996). Incorporation of inexact dynamic optimization with fuzzy relation analysis for integrated climate change impact study. *J. Environ. Manage.*, 48 (1), 45-68. https://dx.doi.org/10.1006/jema.1996.0065

Huang, W., Baetz, B., and Razavi, S. (2016). A GIS-based integer programming approach for the location of solid waste collection depots. *J. Environ. Inf.*, 28(1), 39-44. https://dx.doi.org/10.380 8/jei.201600342

Li, P., Chen, B., Li, Z., and Jing, L. (2016). ASOC: A novel agent-based simulation-optimization coupling approach-algorithm and application in offshore oil spill responses. *J. Environ. Inf.*, 28(2), 90-100. https://dx.doi.org/10.3808/jei.201600354

Li, Y. P. and Huang, G.H. (2009). Fuzzy-stochastic-based violation analysis method for planning water resources management systems with uncertain information. *Inf. Sci.*, 179(24), 4261-4276. https:// dx.doi.org/10.1016/j.ins.2009.09. 001

Li, Y.P., Huang, G.H., and Nie, S.L. (2007). Mixed interval–fuzzy two-stage integer programming and its application to flood-diversion planning. *Eng. Optim.*, 39(2), 163-183. https://dx.doi.org /10.1080/03052150601044831

Li, Y.P., Huang, G.H., and Nie, S.L. (2010). Planning water resources management systems using a fuzzy-boundary interval-stochastic programming method. *Adv. Water Resour.*, 33(9), 1105-1117. https: //dx.doi.org/10.1016/j.advwatres.2010.06.015

Li, Y.P., Huang, G.H., Yang, Z.F., and Nie, S.L. (2008). IFMP: interval-fuzzy multistage programming for water resources management under uncertainty. *Resour. Conserv. Recy.*, 52(5), 800-812. https://dx.doi.org/10.1016/j.resconrec.2007.11.007

Li, Z., Huang, G., Cai, Y., and Li, Y. (2014). Inexact optimization model for supporting waste-load allocation in the Xiangxi River basin of the Three Gorges reservoir region, China. *J. Comput. Civil Eng.*, 29(6), 04014093. https://dx.doi.org/10.1061/(ASCE)CP.1943 -5487.0000426

Li, Z., Huang, G., Yu, H., Zhou, Y., and Huang, W. (2015). Critical factors and their effects on product maturity in food waste composting. *Environ. Monit. Assess.*, 187(4), 217. https://dx.doi. org/10.1007/s10661-015-4430-9

Li, Z., Huang, G., Zhang, Y., and Li, Y. (2013). Inexact two-stage stochastic credibility constrained programming for water quality management. *Resour. Conserv. Recy.*, 73, 122-132. http://dx.doi. org/10.1016/j.resconrec.2013.01.008

Liu, Y., Lai, X., and Chang, G.L. (2006). Two-level integrated optimization system for planning of emergency evacuation. *J. Transp. Eng.*, 132(10), 800-807. https://dx.doi.org/10.1061/(ASCE) 0733-947X(2006)132:10(800)

Lu, H., Huang, G., Zeng, G., Maqsood, I., and He, L. (2008). An inexact two-stage fuzzy-stochastic programming model for water resources management. *Water Resour. Manag.*, 22(8), 991-1016. https://dx.doi.org/10.1007/s11269-007-9206-8

Malesic, M., Prezelj, I., Juvan, J., Polic, M., and Uhan, S. (2015). Evacuation in the event of a nuclear disaster: Planned activity or improvisation? *Int. J. Disaster Risk Reduct.*, 12, 102-111. https:// dx.doi.org/10.1016/j.ijdrr.2014.12.005

Nematian, J. (2016). An extended two-stage stochastic programming approach for water resources management under uncertainty. *J. Environ. Inf.*, 27(2), 72-84. https://dx.doi.org/10.3808/jei.201600334

Nomura, S., Gilmour, S., Tsubokura, M., Yoneoka, D., Sugimoto, A., Oikawa, T., Kami, M., and Shibuya, K. (2013). Mortality risk amongst nursing home residents evacuated after the Fukushima nuclear accident: a retrospective cohort study. *PloS one*, 8(3), e60192. https://dx.doi.org/10.1371/journal.pone.0060192

Pan, X., Han, C.S., Dauber, K., and Law, K.H. (2007). A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations. *AI & Soc.*, 22(2), 113-132. https:// dx.doi.org/10.1007/s00146-007-0126-1

Pedrycz, W. (1994). Why triangular membership functions? *Fuzzy Sets and Systems*, 64(1), 21-30. https://dx.doi.org/10.1016/0165-01 14(94)90003-5

Sheffi, Y., Mahmassani, H., and Powell, W.B. (1982). A transportation network evacuation model. *Transp. Res. Part A*, 16(3), 209-218. https://dx.doi.org/10.1016/0191-2607(82)90022-X

Soni, H.N., and Joshi, M. (2015). EOQ model with backorders under linear combination of possibility and necessity measure. *Int. J. Math. Oper. Res.*, 7(2), 194-214. https://dx.doi.org/10.1504/IJMO R.2015.068292

Tong, L., Saminathan, R., and Chang, C. (2016). Uncertainty assessment of non-normal emission estimates using non-parametric bootstrap confidence intervals. *J. Environ. Inf.*, 28(1), 61-70. https: //dx.doi.org/10.3808/jei.201500322

Tweedie, S.W., Rowland, J.R., Walsh, S.J., Rhoten, R.P., and Hagle, P.I. (1986). A methodology for estimating emergency evacuation times. *Soc. Sci. J.*, 23(2), 189-204. https://dx.doi.org/10.1016/0362 -3319(86)90035-2

Wada, K., Yoshikawa, T., Hayashi, T., and Aizawa, Y. (2012). Emergency response technical work at Fukushima Dai-ichi nuclear power plant: occupational health challenges posed by the nuclear disaster. *Occupational and Environmental Medicine*, http://dx.doi. org/10.1136/oemed-2011-100587

Xie, C., Lin, D.Y., and Waller, S.T. (2010). A dynamic evacuation network optimization problem with lane reversal and crossing elimination strategies. *Transp. Res. Part E*, 46(3), 295-316. https://dx. doi.org/10.1016/j.tre.2009.11.004

Yin, Y., Huang, G., and Hipel, K. (1999). Fuzzy relation analysis for multicriteria water resources management. *J. Water Res. Pl.*, 125 (1), 41-47. https://dx.doi.org/10.1061/(ASCE)0733-9496(1999)125: 1(41)

Zhang, Y., and Huang, G. (2010). Fuzzy robust credibility-constrained d programming for environmental management and planning. *J. Air Waste Manage. Assoc.*, 60(6), 711-721. https://dx.doi.org/10.31 55/1047-3289.60.6.711