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ORIGINAL PAPER

Identification of optimal plans for municipal solid waste management in an environment of fuzziness and two-layer randomness

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Abstract A superiority-inferiority-based inexact fuzzy-stochastic chance-constrained programming (SI-IFSCCP) approach is developed for supporting long-term municipal solid waste management under uncertainty. Through SI-IFSCCP, multiple uncertainties expressed as intervals, possibilistic and probabilistic distributions, as well as their combinations, could be directly communicated into the optimization process, leading to enhanced system robustness. Through tackling fuzziness and two-layer randomness, various subjective judgments of many stakeholders with different interests and preferences could be extensively reflected, guaranteeing a lower degree of biases during data sampling and a higher degree of public acceptance for the generated plans. Two levels of system-violation risk could also be reflected by SI-IFSCCP, reflecting the relationship between economic efficiency and system reliability. A two-step solution method with improved computational efficiency is proposed for SI-IFSCCP. To demonstrate its applicability, the developed methodology is then applied to a long-term municipal solid waste management problem. Useful solutions have been generated. Satisfactory waste flow plans could be identified according to system conditions and policy inclination, supporting in-depth tradeoff analyses between system optimality and reliability as well as between economic and environmental objectives.

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1 Introduction

Due to population growth and economic development, quantities of municipal solid waste (MSW) are on the rise across the world. The problem of meeting rising waste disposal demands with limited facility capacities has been one of the most pressing challenges confronted by municipal authorities. Systems analysis methods and optimization techniques are thus required to assist in identifying cost-effective plans for waste-flow allocation and facility utilization. From a viewpoint of long-term planning, desired MSW management plans may vary with changes in waste-generation rates among different periods (Baetz 1990; Huang et al. 1997; Maqsood et al. 2004). Moreover, precise data is hard to be obtained due to temporal and spatial variations in MSW system conditions; instead, uncertainties are ubiquitous in each system component, creating complexities which are beyond the capabilities of deterministic programming approaches. Thus, it is imperative to employ inexact mathematical programming techniques for supporting long-term MSW management planning under uncertainty.

Over the past two decades, a number of studies were conducted to contend with uncertainties in MSW management systems. Correspondingly, a wide spectrum of inexact optimization techniques were proposed which could be classified into three categories: stochastic mathematical programming (SMP), fuzzy mathematical programming (FMP) and interval mathematical programming (IMP) (Huang et al. 1994, 1995, 1997, 2001; Huang 1998; Chang and Wang 1997; Chanas and Zielinski 2000;

Yeomans et al. 2003; Maqsood et al. 2005; Li et al. 2007; Cai et al. 2009a). Among them, interval-parameter linear programming (ILP) proves to be an effective approach because that it allows uncertainties expressed as interval numbers to be directly communicated into the optimization process and does not lead to complicated intermediate models (Huang et al. 1995). Although ILP has such strengths, it may encounter difficulties when parameters in the model's right-hand sides (b_i) are highly uncertain and expressed as probability distributions (Morgan et al. 1993; Huang 1998). In contrast, chance-constrained programming (CCP) is effective in reflecting probability distributions of b_i, but not so much for uncertainties in left-hand-side coefficients (a_{ij}) and cost coefficients (c_j). Thus, Huang (1998) developed an interval-parameter chance-constrained linear programming (ICCP) approach through the integration of CCP and ILP. It improves upon ILP by allowing distribution information in b_i to be effectively incorporated within its optimization process; it also enhances the capability of CCP by being able to tackling uncertainties in a_{ij} and c_j. Although ICCP is effective in dealing with intervals and probability distributions, several limitations still remain, including: (1) it encounters difficulties when the lower and upper bounds of interval numbers are uncertain; (2) it becomes ineffective when the right-hand coefficients (b_i) are expressed as probability distributions of uncertain numbers; (3) it cannot handle possibilistic distributions (i.e., fuzzy sets) which reflect a series of confidence levels of decision makers when estimating parameter values. Particularly, it is incapable of dealing with fuzzy sets with probabilistic characteristics (i.e., fuzzy random variables) which represent varied subjective judgments on a parameter either from a number of stakeholders or from one stakeholder under different scenarios; (4) it may become useless when any combinations of the above problems exist, especially when multiple formats of uncertainties are concurrently present in one parameter.

On the other hand, in order to address uncertainties expressed as possibilistic distributions (i.e., fuzzy sets), a number of fuzzy linear programming (FLP) approaches were proposed based on fuzzy sets theory. These methods mostly utilize ranking operations (e.g., the area compensation and signed distance methods) or discretize fuzzy sets via α-levels (e.g., robust programming) to defuzzify ambiguous coefficients in an optimization model so as to convert the problem into a corresponding deterministic one (Fortemps and Roubens 1996; Inuiguchi and Sakawa 1998; Chiang 2001). At the same time, a number of fuzzy-stochastic linear programming (FSLP) methods were developed to tackle fuzzy random variables. In these methods, fuzzy random variables are usually defuzzified in the first place and then derandomized through traditional stochastic programming techniques such as the two-stage programming approach (Luhandjula 1996; Van Hop 2007). The major disadvantages of these FSLP approaches lie in that they normally generate a large number of additional constraints and variables, and thus result in complicated and time-consuming computation processes (Van Hop 2007). Recently, Van Hop (2007) proposed a superiority-inferiority-based fuzzy-stochastic linear programming (SI-FSLP) approach as a new attempt to deal with fuzzy random variables. Through this method, relationships among fuzzy/fuzzy-random coefficients are reflected through varying superiority and inferiority degrees (instead of discrete intervals under different α-cut levels), leading to a sharp decline in computational efforts compared to conventional FLP such as robust programming. Also, through quantifying economic penalties of potential constraint violations (due to possibilistic and/or probabilistic uncertainties), the original models could be transformed into equivalent deterministic ones and thus easily solved. Though SI-FSLP is effective in reflecting dual uncertainties expressed as probability distributions of fuzzy sets, it is incapable of addressing independent uncertainties of many parameters that can hardly be available as possibilistic or probabilistic distributions. It is well recognized that, the quality of available information is mostly not satisfactory enough in real-world cases; when uncertainties can only be obtained as intervals without any distribution information, the SI-FSLP approach may become inapplicable. Moreover, SI-FSLP cannot handle uncertainties which are expressed as probability distributions of fuzzy random variables (i.e., fuzzy sets with two-layer randomness) in many real-world problems, resulting in losses of valuable uncertain information.

Therefore, this research is aimed at remedying the above deficiencies and contending with multiple uncertainties existing in MSW management systems. In this study, ILP, CCP and SI-FSLP will be incorporated within a general framework to deal with multiple uncertainties in terms of intervals, probabilistic and possibilistic distributions, as well as their combinations. This will lead to a superiority-inferiority-based inexact fuzzy-stochastic chance-constrained programming (SI-IFSCCP) approach. The proposed approach would help explicitly address multiple uncertainties embedded in MSW management systems without unrealistic simplifications, so that robust solutions could be obtained. Also, it can help examine the relationship between system efficiency and system-violation risk under uncertainty. More importantly, through quantifying the costs of violating constraints by a set of economic penalties under a series of risk levels, satisfactory waste flow plans could be identified with comprehensive considerations over potential system violations, leading to highly enhanced system robustness. The proposed methodology will then be applied to a case study to demonstrate its validness.

2 Statement of problems

A MSW management system is pervaded with uncertainties. Most of its parameters are uncertain in nature and their interrelationships could be extremely complicated. For example, due to the variations in waste characteristics, geographical conditions, employed technologies, land availability and labor prices, costs of waste collection, transportation, treatment and disposal are subject to uncertainties. Also, intrinsic fluctuations of many impact factors, such as waste compositions and operation conditions, may result in uncertainties associated with the capacities of waste management facilities. Particularly, waste generation is highly uncertain since it is affected by many factors, such as economic development, population growth and public policies (Nie et al. 2007). Inevitably, these inherent uncertainties would cause difficulties in parameter estimation. In fact, in long-term MSW management problems, values of parameters are hard to be precisely estimated, while it is more realistic for decision makers to express them as imprecise data based on historic data, expertise and experience. Moreover, uncertainties within MSW management systems could be further compounded by combinations of uncertain information presented in multiple formats (e.g., intervals, possibilistic and probabilitic distributions), leading to amplified intricacies in MSW management.

Particularly, MSW management problems could be viewed from various perspectives depending on the subjectivity of decision makers and technical professionals (Najm et al. 2002). The values of parameters are usually subjectively estimated by decision makers and stakeholders, and thus may merely be obtained as imprecise information, such as fuzzy sets. Because of the subjectivity, the estimated values acquired from different sources may differ from each other. Such deviations in subjective estimations may lead to both fuzziness and randomness within MSW management systems. Moreover, the estimation for some parameters, such as waste generation rates, is of significant importance for the success of optimization efforts. Thus, many stakeholders should be involved and detailed subjective information should be investigated. Consequently, there may even be two-layer randomness (i.e., two layers of probability distributions) embedded within one parameter as described below:

Example 1: The estimation from one decision maker on the same parameter could vary under different scenarios. When being enquired for the lowest waste generation rate of a city in the next 5 years, a decision maker would probably describes it as follows: (a) if the population growth and economic development in this city is slow in the next 5 years (with a probability of 20%), the lowest waste generation rate is roughly 100 ton/day which can be expressed as a fuzzy set ($\widetilde{100}$ ton/day); (b) if the population growth and economic development in this city is medium (with a probability of 60%), the lower bound for the waste generation rate is roughly 140 ton/day (i.e., $\widetilde{140}$ ton/day); (c) if the population growth and economic development is rapid (with a probability of 20%), the corresponding waste generation rate is roughly 180 ton/day (i.e., $\widetilde{180}$ ton/day). Such highly imprecise information can be described as fuzzy random variables. When sufficient fuzzy random variables (i.e., first-layer randomness) are sampled from a large number of decision makers, the lower bound of waste generation rates could then be expressed as a probability distribution of these fuzzy random variables (i.e., second-layer randomness), resulting in fuzziness and two-layer randomness as shown in Fig. 1. Similarly, the upper bound of waste generation rate can also be obtained as a probability distribution of fuzzy random variables.

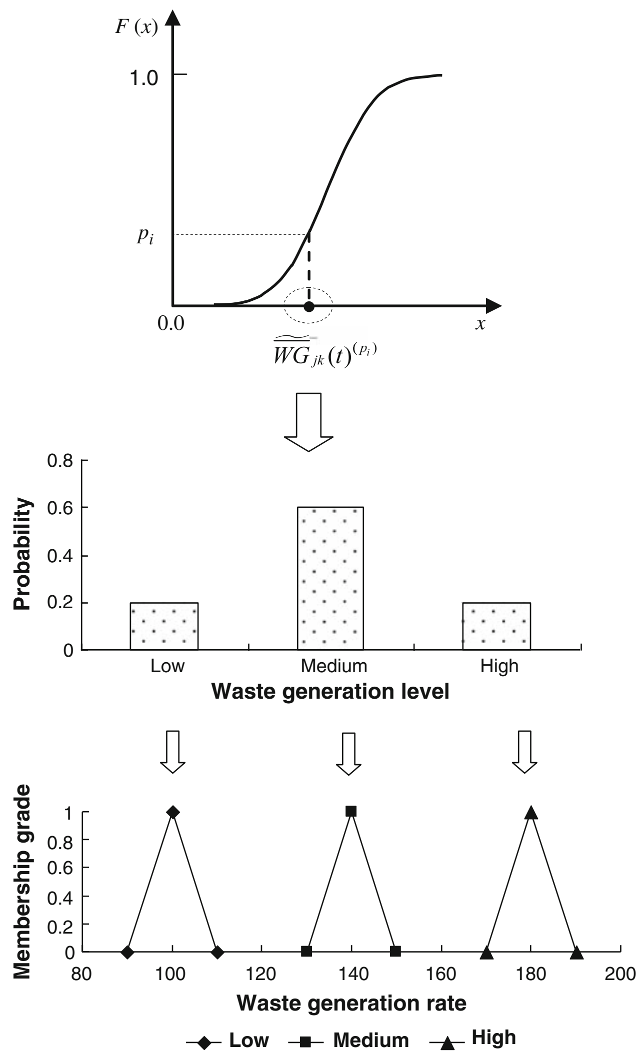

Fig. 1 Fuzziness and two-layer randomness embedded within waste generation rates

Example 2: When being asked for the value of a certain parameter, groups with competing interests have their own perspectives and thus varied estimations. In order to extensively reflect a variety of opinions without prejudices, data for parameter estimation need to be collected from more than one stakeholder group. Firstly, group A of stakeholders (e.g., the waste management division of a local government) is asked to estimate the lowest daily waste generation rate in a city. Within this group, each involved individual has his/her own judgment based on his/her personal experience and preference. Then, individuals in group A may gather as several small groups: (a) 20% of them agree that the waste generation rate would be low, and they reach a consensus that the most possible value would be 100 ton/day; (b) 60% of them believe that there would be a medium generation rate at around 140 ton/day; (c) another 20% support the idea of a high generation rate which is roughly 180 ton/day. Thus, it is more realistic to reflect such differences in subjective judgments within group A as a fuzzy random variable than a deterministic number. Likewise, other groups of stakeholders may give their judgments as fuzzy random variables which differ from that from group A. For example, stakeholders from waste-generating industries may be inclined to underestimate generation rates; while resident representatives would prefer higher values to protect environmental quality. When sufficient fuzzy random variables (i.e., first-layer randomness) are sampled from a large number of stakeholder groups, a probability distribution function of these fuzzy random variables (i.e., second-layer randomness) could be obtained for each bound of the waste generation rate, leading to two layers of randomness (see Fig. 1).

Apparently, such multiple uncertainties and associated complexities are far beyond the capabilities of existing optimization methods, and over-simplification of these uncertain parameters into deterministic ones would make the decision results less useful. These uncertainties are required to be incorporated into the decision-making process to generate robust waste management plans. The more uncertainties reflected through the optimization efforts, the more robust the results would be. Thus, it is imperative to develop advanced inexact optimization approaches to deal with MSW problems in a theoretically sound and practically viable way.

3 Methodology

3.1 Inexact chance-constrained programming

In real-world problems, deterministic numbers are normally hard to be obtained, while the values of a parameter may fluctuate within a range. Such a range with known lower and upper bounds but unknown distribution is defined as an interval number: $a^{\pm} = [a^-, a^+] = \{t \in a | a^- \le t \le a^+\}$, where a^- and a^+ are the lower and upper bounds of $a^{\pm}$, respectively. When $a^- = a^+$, $a^{\pm}$ becomes a deterministic number (Huang et al. 1995). In MSW management systems, many parameters may be obtained as interval numbers (Cai et al. 2007, 2008, 2009b; Tan et al. 2009). For example, the operating cost of a landfill is $[55, 75] per tonne, which means that the cost for disposing one tonne of waste at the landfill is between $55 and 75. Likewise, decision makers mostly feel more confident in specifying the minimum and maximum daily capacities of a waste-to-energy facility than giving a deterministic number.

In ILP, interval numbers are allowed to be modeling inputs and can be directly communicated into the optimization process. According to Huang et al. (1994, 1995), an ILP model is defined as follows:

$$\text{Min} f^{\pm} = C^{\pm} X^{\pm} \tag{1a}$$

subject to:

$$A^{\pm} X^{\pm} \le B^{\pm} \tag{1b}$$

$$X^{\pm} \ge 0 \tag{1c}$$

where $A^{\pm} \in \{\mathbb{R}^{\pm}\}^{m \times n}, B^{\pm} \in \{\mathbb{R}^{\pm}\}^{m \times 1}, C^{\pm} \in \{\mathbb{R}^{\pm}\}^{1 \times n}$, $X^{\pm} \in \{\mathbb{R}^{\pm}\}^{n \times 1}$, and $\mathbb{R}^{\pm}$ denotes a set of interval numbers.

Although ILP allows intervals to be directly communicated into the optimization process, it may encounter difficulties when parameters in the model's right-hand side (b_i) are highly uncertain and can merely be expressed as probability distributions (Morgan et al. 1993; Huang 1998). Thus, chance-constrained programming (CCP) should be introduced. Consider a general stochastic linear programming (SLP) as follows:

$$\text{Min}\ C(t)X \tag{2a}$$

subject to:

$$A(t)X \le B(t) \tag{2b}$$

$$X \ge 0 \tag{2c}$$

where $A(t)$, $B(t)$ and $C(t)$ are sets with random elements defined on a probability space T, $t \in T$ (Charnes et al. 1972; Infanger and Morton 1996). Moreover, $A(t)$, $B(t)$ and $C(t)$ are stochastically independent. To solve this model, the CCP approach converts it to a deterministic version through fixing a certain level of probability $p_i \in [0, 1]$ for the ith $(i = 1, 2,\ldots,m)$ constraint in $A(t)X \le B(t)$ and imposing the condition that the constraint is satisfied with at least a probability of $1 - p_i$. Then, the feasible solution set is subject to the following constraints (Charnes et al. 1972):

$$\Pr[\{t|A_i(t)X \leq b_i(t)\}] \geq 1 - p_i, \quad i = 1, 2, \ldots, m \tag{3}$$

where $A_i(t)X \leq b_i(t)$ is the ith constraint in $A(t)X \leq B(t)$.

According to Huang (1998) and Huang et al. (2001), these constraints are generally nonlinear, and the set of feasible constraints is convex only for some particular cases, one of which is when $A_i(t)$ become deterministic [i.e., $A_i(t) \rightarrow A_i$] and $b_i(t)$ are random. Under such condition, constraint (3) becomes linear:

$$A_i X \leq b_i(t)^{(p_i)}, \quad \forall i \tag{4}$$

where $b_i(t)^{(p_i)}$ is a deterministic number when the cumulative distribution function of b_i [i.e., $F_i(b_i)$] and the probability of violating the ith constraint (i.e., p_i) are both given, and $b_i(t)^{(p_i)} = F_i^{-1}(p_i)$. Equation 4 is linear only when A is deterministic. If both A and B are uncertain, the set of feasible constraints may become more complicated (Ellis 1991; Infanger 1993; Zare and Daneshmand 1995). Also, CCP is unable to handle independent uncertainties in C. In order to better account for uncertainties in A, B and C, Huang (1998) integrated the CCP method into the ILP framework, leading to an interval-parameter chance-constrained programming (ICCP) model as follows:

$$\text{Max} f^{\pm} = C^{\pm}X^{\pm} \tag{5a}$$

subject to:

$$\Pr[\{t|A_i^{\pm}X^{\pm} \leq b_i(t)\}] \geq 1 - p_i, \quad i = 1, 2, \ldots, m \tag{5b}$$

$$x_j^{\pm} \geq 0, \; x_j^{\pm} \in X^{\pm}, \quad j = 1, 2, \ldots, n \tag{5c}$$

where $A_i^{\pm}X^{\pm} \leq b_i(t)$ is the ith constraint in $A^{\pm}X^{\pm} \leq B(t)$. Model (5) can be converted into an "equivalent" deterministic version as follows:

$$\text{Max} f^{\pm} = C^{\pm}X^{\pm} \tag{6a}$$

subject to:

$$A_i^{\pm}X^{\pm} \leq b_i(t)^{(p_i)}, \quad i = 1, 2, \ldots, m \tag{6b}$$

$$x_j^{\pm} \geq 0, \; x_j^{\pm} \in X^{\pm}, \quad j = 1, 2, \ldots, n \tag{6c}$$

3.2 Superiority-inferiority-based fuzzy-stochastic linear programming

Besides interval numbers, uncertainties in MSW management cases may be expressed as fuzzy sets. For example, decision makers might estimate that the most possible value for the operating cost of a facility is \$40 per tonne and there is no possibility for it to be lower than \$30 or more than \$50 per tonne; this can then be expressed as a fuzzy set (i.e., $\widetilde{\$40}$ per tonne). In addition, these fuzzy sets are usually associated with randomness, leading to fuzzy random variables. Fuzzy random variables could result from different subjective judgments upon one parameter from either one decision maker under varied scenarios or from a number of decisions makers.

In order to tackle fuzzy random variables, a superiority-inferiority-based fuzzy-stochastic linear programming (SI-FSLP) approach which was recently proposed by Van Hop (2007) should be introduced. This programming approach is based on a method for comparing fuzzy sets (or fuzzy random variables) through superiority and inferiority degrees. Let $\tilde{G}$ be a family of triangular fuzzy sets which can be defined as follows

$$\tilde{G} = \{\tilde{\delta} = (\delta, a, b), a, b \geq 0\} \text{ and } \mu_{\tilde{\delta}}(x) = \begin{cases} \max\left(0, 1 - \frac{\delta - x}{a}\right) & \text{if } x \leq \delta, a > 0 \\ 1 & \text{if } a = 0 \text{ and/or } b = 0 \\ \max\left(0, 1 - \frac{x - \delta}{b}\right) & \text{if } x > \delta, b > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where scalars a and b ($a, b \geq 0; a, b \in \mathbb{R}$) are named the left and right spreads, respectively. A crisp (i.e., deterministic) number ($\delta \in \mathbb{R}$) can be illustrated as a triangular fuzzy set $\tilde{\delta} = (\delta, 0, 0)$Zimmerman (1991).

Consider two triangular fuzzy sets $\tilde{u} = (u, a, b)$ and $\tilde{v} = (v, c, d) \in \tilde{G}$, where $\tilde{u} \leq \tilde{v}$ (Fig. 2). The α-level set (i.e., α-cut) of $\tilde{u}$ (or $\tilde{v}$) is a crisp subset of X (or X') which can be defined as follows:

$$\tilde{u}_{\alpha} = \{x | \mu_{\tilde{u}}(x) \geq \alpha \text{ and } x \in X\} \tag{8a}$$

$$\tilde{v}_{\alpha} = \{x' | \mu_{\tilde{v}}(x') \geq \alpha \text{ and } x \in X'\} \tag{8b}$$

Since $\tilde{u} \leq \tilde{v}$, we have $\tilde{u}_{\alpha} \leq \tilde{v}_{\alpha}$, and $\sup\{x' : \mu_{\tilde{v}}(x') \geq \alpha\} - \sup\{x : \mu_{\tilde{u}}(x) \geq \alpha\} \geq 0$. Therefore, the total superiority of $\tilde{v}$ over $\tilde{u}$ is defined as the area of $\tilde{v}$ larger than $\tilde{u}$. Mathematically, this area can be presented as follows (Van Hop 2007):

$$S(\tilde{v}, \tilde{u}) = \int_0^1 \{\sup\{x' : \mu_{\tilde{v}}(x') \geq \alpha\} - \sup\{x : \mu_{\tilde{u}}(x) \geq \alpha\}\} d\alpha \tag{9a}$$

Analogously, the inferiority of $\tilde{u}$ to $\tilde{v}$ can be defined as follows:

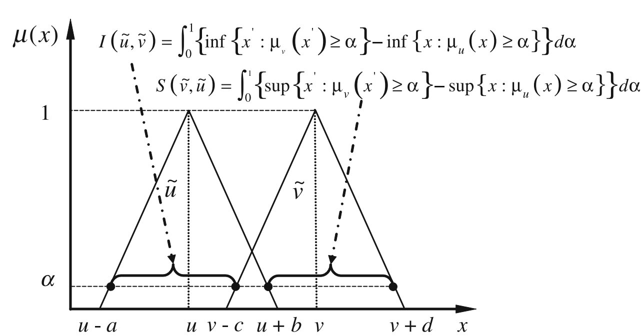

Fig. 2 Superiority and inferiority between $\tilde{u}$ and $\tilde{v}$

$$I(\tilde{u},\tilde{v}) = \int_0^1 \{\inf\{x' : \mu_{\tilde{v}}(x') \geq \alpha\} - \inf\{x : \mu_{\tilde{u}}(x) \geq \alpha\}\} d\alpha \quad (9b)$$

It should be noted that the definitions for superiority and inferiority degrees in Eqs. 9a and b are applicable to not only triangular fuzzy sets, but also other types of fuzzy sets. For triangular fuzzy sets $\tilde{u} = (u,a,b)$ and $\tilde{v} = (v,c,d) \in \tilde{G}$ $(\tilde{u} \leq \tilde{v})$, the superiority of $\tilde{v}$ over $\tilde{u}$ can be further quantified as (Van Hop 2007):

$$S(\tilde{v},\tilde{u}) = v - u + \frac{d-b}{2} \quad (10a)$$

Likewise, the inferiority of $\tilde{u}$ to $\tilde{v}$ can be presented as:

$$I(\tilde{u},\tilde{v}) = v - u - \frac{c-a}{2} \quad (10b)$$

Based on Eqs. 10a and b, the following can be obtained (Van Hop 2007):

$$S(\tilde{f}_j(a_i),\tilde{f}_j(a_k)) \neq I(\tilde{f}_j(a_k),\tilde{f}_j(a_i)) \quad (11)$$

This method can also be extended to measure the superiority and inferiority degrees between two fuzzy random variables. Consider a probabilistic space $(\Omega, \Im, P)$, a fuzzy random variable on this space is a fuzzy set-valued mapping as follows:

$$\tilde{\tilde{X}} : \Omega \rightarrow F_0(\mathbb{R}) \quad (12a)$$

$$\omega \rightarrow \tilde{\tilde{X}}_\omega \quad (12b)$$

For any Borel set ($\boldsymbol{B}$) (Croft et al. 1991) under a α-cut level (between 0 and 1), we have:

$$\tilde{\tilde{X}}_\alpha^{-1}(B) = \{\omega \in \Omega | \tilde{X}_\omega^\alpha \subset B\} \in \Im \quad (13)$$

where $F_0(\mathbb{R})$ and $\tilde{X}_\omega^\alpha$ stand for the set of fuzzy numbers with compact supports and the α-level set of $\tilde{X}_\omega$, respectively; $\tilde{\tilde{X}}$ is a fuzzy random variable if and only if $\omega \in \Omega$; $\tilde{X}_\omega^\alpha$ is a random interval with $\alpha \in (0,1]$ (Luhandjula 1996).

According to Van Hop (2007), for two triangular fuzzy random variables ($\tilde{\tilde{u}} \leq \tilde{\tilde{v}}$), the superiority of fuzzy random variable $\tilde{\tilde{v}}$ over $\tilde{\tilde{u}}$ is:

$$S(\tilde{\tilde{v}},\tilde{\tilde{u}}) = v(\omega) - u(\omega) + \frac{d(\omega) - b(\omega)}{2} \quad (14a)$$

Likewise, the inferiority of fuzzy random variable $\tilde{\tilde{u}}$ to $\tilde{\tilde{v}}$ is:

$$I(\tilde{\tilde{u}},\tilde{\tilde{v}}) = v(\omega) - u(\omega) - \frac{c(\omega) - a(\omega)}{2} \quad (14b)$$

The above method for measuring superiority and inferiority degrees can be utilized to solve fuzzy-stochastic linear programming (FSLP) problems where fuzzy-stochastic coefficients exist in constraints. Consider a FSLP problem as follows:

$$\text{Max } CX \quad (15a)$$

subject to:

$$\tilde{\tilde{A}}X \leq \tilde{\tilde{B}} \quad (15b)$$

$$X \geq 0 \quad (15c)$$

where $C \in \{\mathbb{R}\}^{1\times n}$, $\tilde{\tilde{A}} \in \{\Re\}^{m\times n}$, $\tilde{\tilde{B}} \in \{\Re\}^{m\times 1}$, $\mathbb{R}$ denotes a set of real numbers (i.e., deterministic numbers), and $\Re$ denotes a set of fuzzy random coefficients defined on a probability space (Ω, F, P). This problem requires a maximized objective function value subject to a superiority of the right-hand sides (RHS) over the left-hand sides (LHS) and an inferiority of LHS to RHS. Based on the concepts of superiority and inferiority degrees, problem (15) can be reformulated by applying penalty costs to the violated constraints as caused by variations in fuzziness and randomness. This corresponds to a maximized objective function value subject to penalty costs for any violations of superiority of RHS over LHS or inferiority of LHS to RHS. The equivalent deterministic program for problem (15) is:

$$\text{Max} \sum_{j=1}^{n} c_j x_j - \sum_{i=1}^{m} \beta_i E[\lambda_i^s(\omega)] - \sum_{i=1}^{m} \gamma_i E[\lambda_i^I(\omega)] \quad (16a)$$

subject to:

$$S_i\left(\sum_{j=1}^{n} (\tilde{a}_{ij})_\omega x_j (\tilde{b}_i)_\omega\right) = \lambda_i^S(\omega) \quad i = 1,2,\ldots,m \quad (16b)$$

$$I_i\left((\tilde{b}_i)_\omega, \sum_{j=1}^{n} (\tilde{a}_{ij})_\omega x_j\right) = \lambda_i^I(\omega) \quad i = 1,2,\ldots,m \quad (16c)$$

$$x_j \geq 0 \quad (16d)$$

$$\omega \in \Omega \quad (16e)$$

where $\beta_i > 0$ and $\gamma_i > 0$ are penalty coefficients, E denotes the expected value. The penalty coefficients are introduced to quantify adverse impacts caused by constraint violations as monetary values. Higher penalty costs would correspond to stricter policies in terms of constraint violations. Therefore, decision makers can identify suitable penalty levels based on projected applicable conditions. For example, in an optimistic case (i.e., constraint violations would not lead to significant losses), the decision makers can have β_i and γ_i be lower values; comparatively, in a pessimistic case (i.e., constraint violations would result in severe consequences), the values of β_i and γ_i should be higher. Since the superiority and inferiority degrees (rather than intervals at different α-cut levels) are used to defuzzify the uncertainties, the number of constraints in the resulting deterministic model can be drastically reduced. Also, the comparisons between fuzzy (random) coefficients through analyzing their relative relationships would help relax the constraints. The larger spreads of fuzzy numbers, the higher level of relaxation (Van Hop 2007).

3.3 Superiority-inferiority-based inexact fuzzy-stochastic chance-constrained programming

ICCP or SI-FSLP alone does not suffice for realistically reflecting multiple uncertainties within MSW management problems. Both of them suffer from shortcomings. Although SI-FSLP is capable of tackling possibilistic and probabilistic distributions in constraints, it becomes ineffective when (a) there are uncertainties existing in the objection function; (b) the quality of information is not satisfactory enough as specified distributions. Likewise, ICCP is able to deal with intervals in a_{ij} and c_j as well as probability distributions in b_i, but it encounters difficulties when (a) the lower and upper bounds of intervals are subject to fuzziness and randomness; (b) the right-hand coefficients (b_i) are merely available as uncertain numbers under varied probability levels. It is recognized that, in real-world MSW management problems, it may be hard to acquire deterministic lower and upper bounds for many interval parameters; instead, the two bounds may merely be available as fuzzy random variables, leading to multiple uncertainties as shown in Fig. 3. Such intervals with fuzzy-random bounds can be named as fuzzy-random boundary intervals (FRBIs). Moreover, under some circumstances, there may even be two-layer randomness embedded within the two bounds of intervals (see Fig. 1). Apparently, such problems where two bounds of the intervals possess features of fuzziness and randomness (and/or two-layer randomness) are far beyond the capabilities of ICCP or SI-FSLP.

Thus, in order to contend with the prescribed multiple uncertainties, ILP, CCP and SI-FSLP should be integrated into a general framework. Correspondingly, a superiority-inferiority-based inexact fuzzy-stochastic chance-constrained programming (SI-IFSCCP) model can be proposed as follows:

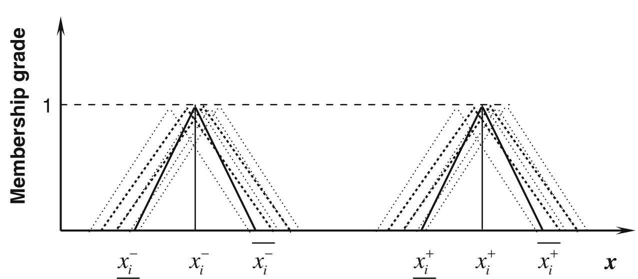

Fig. 3 Fuzzy-random boundaries for interval $x_i^{\pm}$

$$\text{Min} f^{\pm} = C^{\pm} X^{\pm} \tag{17a}$$

subject to:

$$A_r^{\pm} X^{\pm} \leq b_r^{\pm} \quad r \in M,\ r \neq s \tag{17b}$$

$$\tilde{A}_s^{\pm} X^{\pm} \leq \tilde{b}_s^{\pm}(t)^{(p_i)} \quad s \in M,\ s \neq r \tag{17c}$$

$$X^{\pm} \geq 0 \tag{17d}$$

where $C^{\pm} \in \{\mathbb{R}^{\pm}\}^{1\times n}$, $A_r^{\pm} \in \{\mathbb{R}^{\pm}\}^{r\times n}$, $b_r^{\pm} \in \{\mathbb{R}^{\pm}\}^{r\times 1}$, $\tilde{A}_s^{\pm} \in \{\Re^{\pm}\}^{s\times n}$, $\tilde{b}_s^{\pm}(t)^{(p_s)} \in \{\Re^{\pm}\}^{s\times 1}$, $M = (1,\ 2,\ldots,m)$, $\tilde{b}_s^{\pm}(t)^{(p_s)}$ represents corresponding values given the cumulative distribution function of $\tilde{b}_s^{\pm}$ and the probability of violating constraint s (i.e., p_i), $\mathbb{R}^{\pm}$ denotes a set of interval numbers, and $\Re^{\pm}$ denotes a set of intervals with fuzzy-random lower and upper bounds which are named "fuzzy-random boundary interval (FRBI)". Figure 4 illustrates the framework of the proposed SI-IFSCCP model.

The developed SI-IFSCCP model can be solved through a two-step interactive solution method. It is assumed that the lower and upper bounds of intervals have no intersections and they are mutually independent. The SI-IFSCCP model should be firstly transformed into two submodels; each submodel is then converted into a conventional linear program. When the objective function is to be minimized, a submodel corresponding to f^- should be firstly formulated as follows (assume that $b_i^{\pm} > 0$, and $f^{\pm} > 0$):

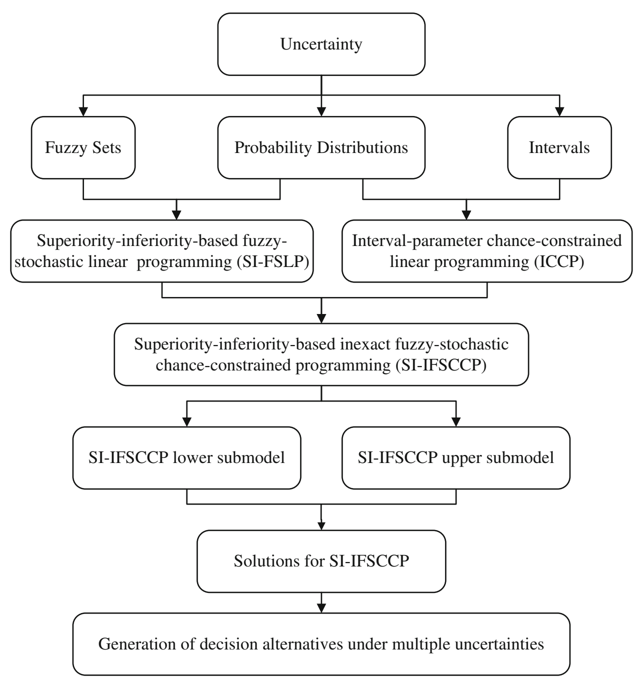

Fig. 4 Schematic diagram of the SI-IFSCCP method

$$\text{Min} f^- = \sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n} c_j^- x_j^+ \tag{18a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}|^+ \text{Sign}(a_{rj}^+) x_j^- + \sum_{j=k_1+1}^{n} |a_{rj}|^- \text{Sign}(a_{rj}^-) x_j^+ \le b_r^+ \quad \forall r,\ r \neq s \tag{18b}$$

$$\sum_{j=1}^{k_1} \left|\tilde{a}_{sj(\omega)}\right|^+ \text{Sign}\left(\tilde{a}_{sj(\omega)}^+\right) x_j^- + \sum_{j=k_1+1}^{n} |\tilde{a}_{sj(\omega)}|^- \text{Sign}(\tilde{a}_{sj(\omega)}^-) x_j^+ \le \tilde{b}_{s(\omega)}^+ (t)^{(p_i)} \quad \forall s, s \neq r \tag{18c}$$

$$x_j^\pm \ge 0, \quad \forall j \tag{18d}$$

$$\omega \in \Omega \tag{18e}$$

where $|a_{rj}|^-$ and $|a_{rj}|^+$ represent the lower and upper bounds of the absolute value of $a_{rj}^\pm$, respectively; Sign $(a_{rj}^\pm)$ is the sign of $a_{rj}^\pm$ [i.e., Sign $(a_{rj}^\pm) = 1$ when $a_{rj}^\pm \ge 0$; Sign $(a_{rj}^\pm) = -1$ when $a_{rj}^\pm < 0$]; $x_j^\pm$, $j = 1, 2,\ldots,k_1$, are interval variables with positive coefficients in the objective function, and $x_j^\pm$, $j = k_1 + 1,\ k_1 + 2,\ldots,n$, are interval variables with negative coefficients (Huang et al. 1995). Then, submodel (18) can be transformed into a deterministic linear programming model as follows:

$$\text{Min} \sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n} c_j^- x_j^+ + \sum_{i=1}^{m} \beta_i E[\lambda_i^S(\omega)^-] + \sum_{i=1}^{m} \gamma_i E[\lambda_i^I(\omega)^-] \tag{19a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}|^+ \text{Sign}(a_{rj}^+) x_j^- + \sum_{j=k_1+1}^{n} |a_{rj}|^- \text{Sign}(a_{rj}^-) x_j^+ \le b_r^+ \quad \forall r \tag{19b}$$

$$S_i\left(\sum_{j=1}^{k_1} (|\tilde{a}_{sj(\omega)}|^+) \text{Sign}(\tilde{a}_{sj(\omega)}^+) x_j^- + \sum_{j=k_1+1}^{n} (|\tilde{a}_{sj(\omega)}|^-) \times \text{Sign}(\tilde{a}_{sj(\omega)}^-) x_j^+, \tilde{b}_{s(\omega)}^+ (t)^{(p_i)}\right) = \lambda_i^S(\omega)^- \quad \forall s \tag{19c}$$

$$I_i\left(\tilde{b}_{s(\omega)}^+ (t)^{(p_i)}, \sum_{j=1}^{k_1} (|\tilde{a}_{sj(\omega)}|^+) \text{Sign}(\tilde{a}_{sj(\omega)}^+) x_j^- + \sum_{j=k_1+1}^{n} (|\tilde{a}_{sj(\omega)}|^-) \text{Sign}(\tilde{a}_{sj(\omega)}^-) x_j^+\right) = \lambda_i^I(\omega)^- \quad \forall s \tag{19d}$$

$$x_j^\pm \ge 0 \quad \forall j \tag{19e}$$

$$\lambda_i^S(\omega)^-, \lambda_i^I(\omega)^- \ge 0 \quad i = 1, 2, \ldots, m \tag{19f}$$

$$\omega \in \Omega \tag{19g}$$

Solutions of $x_{j\,\text{opt}}^-$ ($j = 1, 2,\ldots,k_1$) and $x_{j\,\text{opt}}^+$ ($j = k_1 + 1, k_1 + 2,\ldots,n$) can be obtained through the above submodel. Thus, the submodel corresponding to f^+ can be formulated as follows (assuming that $b_i^\pm > 0$, and $f^\pm > 0$):

$$\text{Min} f^+ = \sum_{j=1}^{k_1} \tilde{c}_{j(\omega)}^+ x_j^+ + \sum_{j=k_1+1}^{n} \tilde{c}_{j(\omega)}^+ x_j^- \tag{20a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}|^- \text{Sign}(a_{rj}^-) x_j^+ + \sum_{j=k_1+1}^{n} |a_{rj}|^+ \text{Sign}(a_{rj}^+) x_j^- \le b_r^- \quad \forall r, r \neq s \tag{20b}$$

$$\sum_{j=1}^{k_1} (|\tilde{a}_{sj(\omega)}|^-) \text{Sign}(\tilde{a}_{sj(\omega)}^-) x_j^+ + \sum_{j=k_1+1}^{n} (|\tilde{a}_{sj(\omega)}|^+) \text{Sign}(\tilde{a}_{sj(\omega)}^+) x_j^- \le \tilde{b}_{s(\omega)}^- (t)^{(p_i)} \quad \forall s, s \neq r \tag{20c}$$

$$x_j^\pm \ge 0 \quad \forall j \tag{20d}$$

$$x_j^+ \ge x_{j\text{opt}}^- \quad j = 1, 2, \ldots, k_1 \tag{20e}$$

$$x_j^- \le x_{j\text{opt}}^+ \quad j = k_1 + 1,\ k_1 + 2, \ldots, n \tag{20f}$$

$$\omega \in \Omega \tag{20g}$$

Similarly, submodel (20) can be transformed into a deterministic model as follows:

$$\text{Min} \sum_{j=1}^{k_1} \tilde{c}_{j(\omega)}^+ x_j^+ + \sum_{j=k_1+1}^{n} \tilde{c}_{j(\omega)}^+ x_j^- + \sum_{i=1}^{m} \beta_i E[\lambda_i^S(\omega)^+] + \sum_{i=1}^{m} \gamma_i E[\lambda_i^I(\omega)^+] \tag{21a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{rj}|^- \text{Sign}(a_{rj}^-) x_j^+ + \sum_{j=k_1+1}^{n} |a_{rj}|^+ \text{Sign}(a_{rj}^+) x_j^- \le b_r^- \quad \forall r \tag{21b}$$

$$S_i\left(\sum_{j=1}^{k_1} (|\tilde{a}_{sj(\omega)}|^-) \text{Sign}(\tilde{a}_{sj(\omega)}^-) x_j^+ + \sum_{j=k_1+1}^{n} (|\tilde{a}_{sj(\omega)}|^+) \times \text{Sign}(\tilde{a}_{sj(\omega)}^+) x_j^-, \tilde{b}_{s(\omega)}^- (t)^{(p_i)}\right) = \lambda_i^S(\omega)^+ \quad \forall s \tag{21c}$$

$$I_i\left(\tilde{b}^-_{s(\omega)}(t)^{(p_i)}, \sum_{j=1}^{k_1}(|\tilde{a}_{sj(\omega)}|^-)\text{Sign}(\tilde{a}^-_{sj(\omega)})x^+_j + \sum_{j=k_1+1}^{n}(|\tilde{a}_{sj(\omega)}|^+)\text{Sign}(\tilde{a}^+_{sj(\omega)})x^-_j\right) = \lambda^I_i(\omega)^+ \quad \forall s \tag{21d}$$

$$x^\pm_j \geq 0 \quad \forall j \tag{21e}$$

$$x^+_j \geq x^-_{jopt} \quad j = 1, 2, \ldots, k_1 \tag{21f}$$

$$x^-_j \leq x^+_{jopt} \quad j = k_1 + 1, k_1 + 2, \ldots, n \tag{21g}$$

$$\lambda^S_i(\omega)^+, \lambda^I_i(\omega)^+ \geq 0 \quad i = 1, 2, \ldots, m \tag{21h}$$

$$\omega \in \Omega \tag{21i}$$

Hence, solutions of $x^+_{j\,\text{opt}}$ ($j = 1, 2,\ldots,k_1$) and $x^-_{j\,\text{opt}}$ ($j = k_1 + 1, k_1 + 2,\ldots,n$) can be obtained from submodel (21). By combining solutions from the two submodels, we have the final solution for model (17): $f^\pm_{\text{opt}} = [f^-_{\text{opt}}, f^+_{\text{opt}}]$ and $x^\pm_{jopt} = [x^-_{jopt}, x^+_{jopt}]$. The above algorithm can be summarized as follows:

- Step 1: Formulate the SI-IFSCCP model according to (17).
- Step 2: Select a significance level p_i, and $\tilde{\tilde{b}}^\pm_s(t)^{(p_i)}$ values can then be obtained according to the given distribution information of $\tilde{\tilde{b}}^-_s(t)$ and $\tilde{\tilde{b}}^+_s(t)$.
- Step 3: Formulate f^- submodel:
  - (a) formulate the objective function according to (18a);
  - (b) formulate the constraints according to (18b) and (18c).
- Step 4: Convert f^- submodel to an equivalent deterministic one:
  - (a) calculate superiority and inferiority degrees for the constraints with FRBI coefficients [i.e., those corresponding to (18c)] according to (19c) and (19d).
  - (b) introduce penalty coefficients and formulate new objective function for f^- submodel according to (19a).
- Step 5: Solve f^- submodel:
  - (a) obtain x^-_{jopt} ($j = 1, 2,\ldots,k_1$) and x^+_{jopt} ($j = k_1 + 1, k_1 + 2,\ldots,n$);
  - (b) obtain f^-_{opt}.
- Step 6: Formulate f^+ submodel:
  - (a) formulate the objective function according to (20a);
  - (b) formulate the first set of constraints according to (20b) and (20c);
  - (c) formulate the second set of constraints for the bounds of decision variables according to (20e) and (20f).
- Step 7: Convert f^+ submodel to an equivalent deterministic one:
  - (a) calculate superiority and inferiority degrees for the constraints with FRBI coefficients [i.e., those corresponding to (20c)] according to (21c) and (21d).
  - (b) introduce penalty coefficients and formulate new objective function for f^+ submodel according to (21a).
- Step 8: Solve f^+ submodel:
  - (a) obtain x^+_{jopt} ($j = 1, 2,\ldots,k_1$) and x^-_{jopt} ($j = k_1 + 1, k_1 + 2,\ldots,n$);
  - (b) obtain f^+_{opt}.
- Step 9: The final solutions can be obtained as: $f^\pm_{\text{opt}} = [f^-_{\text{opt}}, f^+_{\text{opt}}]$ and $x^\pm_{jopt} = [x^-_{jopt}, x^+_{jopt}]$.
- Step 10: Stop.

4 Application

4.1 Overview of the study system

The developed methodology is applied to a long-term MSW management problem, wherein regional waste managers are responsible for allocating waste flows from three cities to two treatment/disposal facilities, as shown in Fig. 5. This case is developed based on representative cost and technical data obtained from a number of solid waste management literature (Huang et al. 1995, 2001; Chang and Wang 1997; Maqsood et al. 2004; Nie et al. 2007; Li et al. 2007). The planning horizon is 15 years, which is further discretized into 3 time periods with 5 years each. Over the planning horizon, an existing landfill and a waste-to-energy (WTE) facility are available to serve the waste treatment/disposal needs. The landfill has an overall cumulative capacity of [4.58, 4.63] × 10^6 ton, while the WTE has a daily capacity of [550, 590] ton/day. The WTE facility generates residues of approximately 20–40% (on a mass basis) of the incoming waste stream; these residues are transported to the landfill for final disposal. Revenue from the produced energy of the WTE facility is approximately $[15, 25] per tonne combusted.

The costs for waste transportation and treatment change temporally and spatially. In this study, they are available as interval numbers according to historical data and empirical experience. For example, the operating cost of the WTE

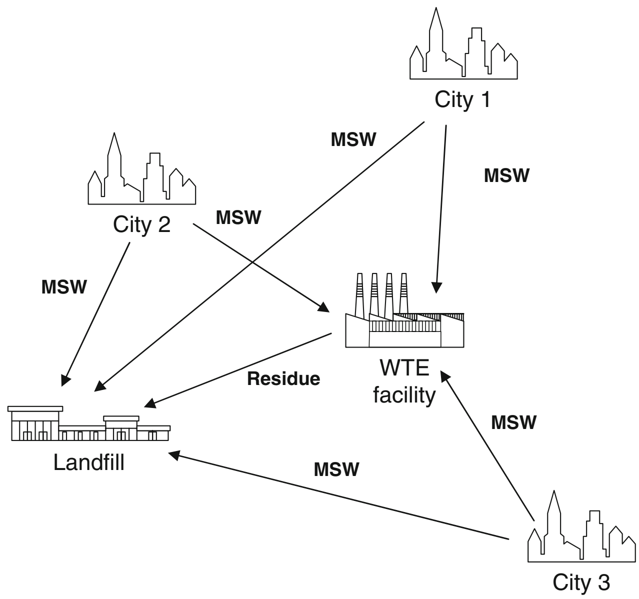

Fig. 5 The study system

facility in period 1 would be $[55, 75] per tonne; the cost for shipping the waste from city 1 to the landfill in period 1 would be $[12.1–16.1] per tonne. Table 1 contains the operating costs of the two facilities and the transportation costs for waste flows from the cities to the facilities as well as for residues from the WTE facility to the landfill during the three periods.

Also, the waste generation rates vary among different cities and different periods. Since waste-generation rates are of significant importance for the identification of desired waste allocation plans, many decision makers and stakeholders should be involved to estimate their values. During data sampling, each stakeholder would be enquired

Table 1 Transportation costs and facility-operation costs

	Time period		
	$k = 1$	$k = 2$	$k = 3$
Cost of waste transportation to landfill, $TR^{\pm}_{1jk}$ ($/ton):			
City 1	[12.1, 16.1]	[13.3, 17.7]	[14.6, 19.5]
City 2	[10.5, 14.0]	[11.6, 15.4]	[12.8, 16.9]
City 3	[12.7, 17.0]	[14.0, 18.7]	[15.4, 20.6]
Cost of waste transportation to landfill, $FT^{\pm}_{k}$ ($/ton):			
Waste-to-energy facility	[9, 11]	[11, 13]	[13, 15]
Cost of waste transportation to WTE facility, $TR^{\pm}_{2jk}$ ($/ton):			
City 1	[9.6, 12.8]	[10.6, 14.1]	[11.7, 15.5]
City 2	[10.1, 13.4]	[11.1, 14.7]	[12.2, 16.2]
City 3	[8.8, 11.7]	[9.7, 12.8]	[10.6, 14.0]
Operating cost, $OP^{\pm}_{ik}$ ($/ton):			
Landfill	[30, 45]	[40, 60]	[50, 80]
Waste-to-energy facility	[55, 75]	[60, 85]	[65, 95]

for the lower bound of the waste generation rate in city j during period k (i.e., $\widetilde{WG}^{-}_{jk}$) under three scenarios: (a) low waste generation level (with a probability of 20%); (b) medium waste generation level (with a probability of 60%); (c) high waste generation level (with a probability of 20%). Thus, the information provided by each stakeholder would then be expressed as a fuzzy random variable ($\widetilde{\overline{WG}}^{-}_{jk}$). When sufficient data of $\widetilde{\overline{WG}}^{-}_{jk}$ are sampled from a large number of stakeholders, a probability distribution function for the lower bound of waste generation rate in city j during period k could be obtained as $\widetilde{\overline{WG}}^{-}_{jk}(t)$. Similarly, the upper bound of the waste generation rate in city j during period k can also be obtained as a probability distribution of fuzzy random variables (i.e., $\widetilde{\overline{WG}}^{+}_{jk}(t)$). In Tables 2 and 3, the cumulative distribution functions for the lower- and upper-bounds of waste generation rates in the three cities over the planning horizon are displayed, respectively.

Although waste generation rates are available as imprecise data, it would be unrealistic to assume that a city could capture all of its generated waste for treatment and disposal. It is acknowledged that, not all of the estimated waste would be actually collected or transported to the treatment/disposal facilities. This can be attributed to: (a) the implementation of policies promoting recycling and reusing; (b) the advancement of source reduction/minimization measures; and (c) the inefficiency in waste collection and transportation systems. To reflect the reductions in waste flows caused by the above reasons, a waste collection factor is introduced in this study as a modification coefficient. Waste collection factors may be affected by a number of impact factors. For example, the implementation of recycling and reusing strategies would lead to an increase in waste collection factors, while the improvement in the efficiency of waste collection/transportation systems would decrease their values. In this case, waste collection factors of the three cities in the three time periods are obtained as fuzzy-random boundary intervals as listed in Table 4.

Therefore, the problem under consideration can be described as follows: given the quantities of waste generated in the cities, the locations and capacities of existing facilities, and the cost structure (including the costs for transportation and operation, as well as the revenues from energy recovery), find out how waste should be routed, processed and disposed so that the overall cost of the system can be minimized under a number of environmental, economic and treatment/disposal constraints. Since multiple formats of uncertainties exist within the system in terms of intervals, possibilistic and probabilistic distributions, as well as their combinations, the SI-IFSCCP method is considered to be a feasible approach for tackling this planning problem.

Table 2 Distribution information of $\widetilde{\widetilde{WG}}_{jk}^{-}(t)$

P_i value	0	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99	1
Period 1											
$\widetilde{\widetilde{WG}}_{11}^{-}$											
L	181[a]	188	204	216	232	244	255	272	284	300	305
M	187	194	210	222	238	250	261	278	290	306	311
H	193	200	216	228	244	256	267	284	296	312	317
$\widetilde{\widetilde{WG}}_{21}^{-}$											
L	81	88	104	116	132	144	155	172	184	200	205
M	87	94	110	122	138	150	161	178	190	206	211
H	93	100	116	128	144	156	167	184	196	212	217
$\widetilde{\widetilde{WG}}_{31}^{-}$											
L	181	188	204	216	232	244	255	272	284	300	305
M	187	194	210	222	238	250	261	278	290	306	311
H	193	200	216	228	244	256	267	284	296	312	317
Period 2											
$\widetilde{\widetilde{WG}}_{12}^{-}$											
L	231	238	254	266	282	294	305	322	334	350	355
M	237	244	260	272	288	300	311	328	340	356	361
H	243	250	266	278	294	306	317	334	346	362	367
$\widetilde{\widetilde{WG}}_{22}^{-}$											
L	106	113	129	141	157	169	180	197	209	225	230
M	112	119	135	147	163	175	186	203	215	231	236
H	118	125	141	153	169	181	192	209	221	237	242
$\widetilde{\widetilde{WG}}_{32}^{-}$											
L	181	188	204	216	232	244	255	272	284	300	305
M	187	194	210	222	238	250	261	278	290	306	311
H	193	200	216	228	244	256	267	284	296	312	317
Period 3											
$\widetilde{\widetilde{WG}}_{13}^{-}$											
L	281	288	304	316	332	344	355	372	384	400	405
M	287	294	310	322	338	350	361	378	390	406	411
H	293	300	316	328	344	356	367	384	396	412	417
$\widetilde{\widetilde{WG}}_{23}^{-}$											
L	131	138	154	166	182	194	205	222	234	250	255
M	137	144	160	172	188	200	211	228	240	256	261
H	143	150	166	178	194	206	217	234	246	262	267
$\widetilde{\widetilde{WG}}_{33}^{-}$											
L	231	238	254	266	282	294	305	322	334	350	355
M	237	244	260	272	288	300	311	328	340	356	361
H	243	250	266	278	294	306	317	334	346	362	367

L a low waste generation level at a probability of 20%, *M* a medium waste generation level at a probability of 60%, *H* a high waste generation level at a probability of 20%

[a] Triangular fuzzy set $\tilde{\delta} = (\delta, a, b)$, where $a = b = 2$. For example, $\tilde{\delta} = \widetilde{137} = (137,\ 2,\ 2)$, where $\delta = 137$ when $\alpha = 1$; $\underline{\delta} = 135$ and $\overline{\delta} = 139$ when $\alpha = 0$

Table 3 Distribution information of $\widetilde{\widetilde{WG}}_{jk}^{+}(t)$

P_i value	0	0.01	0.05	0.1	0.25	0.5	0.75	0.9	0.95	0.99	1
Period 1											
$\widetilde{\widetilde{WG}}_{11}^{+}$											
L	231[a]	238	254	266	282	294	305	322	334	350	355
M	237	244	260	272	288	300	311	328	340	356	361
H	243	250	266	278	294	306	317	334	346	362	367
$\widetilde{\widetilde{WG}}_{21}^{+}$											
L	131	138	154	166	182	194	205	222	234	250	255
M	137	144	160	172	188	200	211	228	240	256	261
H	143	150	166	178	194	206	217	234	246	262	267
$\widetilde{\widetilde{WG}}_{31}^{+}$											
L	231	238	254	266	282	294	305	322	334	350	355
M	237	244	260	272	288	300	311	328	340	356	361
H	243	250	266	278	294	306	317	334	346	362	367
Period 2											
$\widetilde{\widetilde{WG}}_{12}^{+}$											
L	281	288	304	316	332	344	355	372	384	400	405
M	287	294	310	322	338	350	361	378	390	406	411
H	293	300	316	328	344	356	367	384	396	412	417
$\widetilde{\widetilde{WG}}_{22}^{+}$											
L	156	163	179	191	207	219	230	247	259	275	280
M	162	169	185	197	213	225	236	253	265	281	286
H	168	175	191	203	219	231	242	259	271	287	292
$\widetilde{\widetilde{WG}}_{32}^{+}$											
L	231	238	254	266	282	294	305	322	334	350	355
M	237	244	260	272	288	300	311	328	340	356	361
H	243	250	266	278	294	306	317	334	346	362	367
Period 3											
$\widetilde{\widetilde{WG}}_{13}^{+}$											
L	331	338	354	366	382	394	405	422	434	450	455
M	337	344	360	372	388	400	411	428	440	456	461
H	343	350	366	378	394	406	417	434	446	462	467
$\widetilde{\widetilde{WG}}_{23}^{+}$											
L	181	188	204	216	232	244	255	272	284	300	305
M	187	194	210	222	238	250	261	278	290	306	311
H	193	200	216	228	244	256	267	284	296	312	317
$\widetilde{\widetilde{WG}}_{33}^{+}$											
L	281	288	304	316	332	344	355	372	384	400	405
M	287	294	310	322	338	350	361	378	390	406	411
H	293	300	316	328	344	356	367	384	396	412	417

L a low waste generation level at a probability of 20%, *M* a medium waste generation level at a probability of 60%, *H* a high waste generation level at a probability of 20%

[a] Triangular fuzzy set $\tilde{\delta} = (\delta, a, b)$, where $a = b = 2$. For example, $\tilde{\delta} = \widetilde{137} = (137,\ 2,\ 2)$, where $\delta = 137$ when $\alpha = 1$; $\underline{\delta} = 135$ and $\overline{\delta} = 139$ when $\alpha = 0$

Table 4 Waste collection factors ($\tilde{\tilde{\theta}}_{ijk}^{\pm}$) of the three cities in the three periods

Collection factor	Generation level	Probability	Period 1 (k = 1)	Period 2 (k = 2)	Period 3 (k = 3)
$\tilde{\tilde{\theta}}_{1k}^{\pm}$ (city 1)[a]	Low	20%	$[\widetilde{0.12}, \widetilde{0.22}]$	$[\widetilde{0.07}, \widetilde{0.17}]$	$[\widetilde{0.02}, \widetilde{0.12}]$
	Medium	60%	$[\widetilde{0.15}, \widetilde{0.25}]$	$[\widetilde{0.10}, \widetilde{0.20}]$	$[\widetilde{0.05}, \widetilde{0.15}]$
	High	20%	$[\widetilde{0.18}, \widetilde{0.28}]$	$[\widetilde{0.13}, \widetilde{0.23}]$	$[\widetilde{0.08}, \widetilde{0.18}]$
$\tilde{\tilde{\theta}}_{2k}^{\pm}$ (city 2)[a]	Low	20%	$[\widetilde{0.14}, \widetilde{0.24}]$	$[\widetilde{0.12}, \widetilde{0.22}]$	$[\widetilde{0.08}, \widetilde{0.18}]$
	Medium	60%	$[\widetilde{0.17}, \widetilde{0.27}]$	$[\widetilde{0.15}, \widetilde{0.25}]$	$[\widetilde{0.11}, \widetilde{0.21}]$
	High	20%	$[\widetilde{0.20}, \widetilde{0.30}]$	$[\widetilde{0.18}, \widetilde{0.28}]$	$[\widetilde{0.14}, \widetilde{0.24}]$
$\tilde{\tilde{\theta}}_{3k}^{\pm}$ (city 3)[a]	Low	20%	$[\widetilde{0.16}, \widetilde{0.26}]$	$[\widetilde{0.13}, \widetilde{0.23}]$	$[\widetilde{0.10}, \widetilde{0.20}]$
	Medium	60%	$[\widetilde{0.19}, \widetilde{0.29}]$	$[\widetilde{0.16}, \widetilde{0.26}]$	$[\widetilde{0.13}, \widetilde{0.23}]$
	High	20%	$[\widetilde{0.22}, \widetilde{0.32}]$	$[\widetilde{0.19}, \widetilde{0.29}]$	$[\widetilde{0.16}, \widetilde{0.26}]$

[a] Triangular fuzzy set $\tilde{\delta} = (\delta, a, b)$, where $a = b = 0.01$. For example, $\tilde{\delta} = \widetilde{0.15} = (0.15, 0.01, 0.01)$, where $\delta = 0.15$ when $\alpha = 1$; $\underline{\delta} = 0.14$ and $\overline{\delta} = 0.16$ when $\alpha = 0$

This problem will be firstly formulated and solved through a SI-IFSCCP model, and then the SI-IFSCCP solutions will be compared with those obtained from several alternative methods to show the advantage of the developed methodology.

4.2 Modeling formulation

For such a municipal solid waste management system, the decision variables represent waste flows from city j to waste management facility i in period k, denoted as x_{ijk} (ton/day). The objective is to minimize net system cost through aptly allocating the waste flows from the three cities to the two management facilities. The total system cost equals to the summation of waste collection/transportation costs and facility operating costs minus the revenues of the recovered energy from the WTE facility. The constraints involve all of the relationships among the decision variables and the waste generation/management conditions. Consequently, based on data availability, a SI-IFSCCP model can be formulated as follows:

1. Objective function

$$\text{Min} f^{\pm} = 1,825 \sum_{j=1}^{3} \sum_{k=1}^{3} \left\{ \sum_{i=1}^{2} x_{ijk}^{\pm} (TR_{ijk}^{\pm} + OP_{ik}^{\pm}) + x_{2jk}^{\pm} [FE^{\pm} (FT_k^{\pm} + OP_{1k}^{\pm}) - RE_k^{\pm}] \right\} \tag{22a}$$

2. Constraints

(1) Waste disposal demand constraints

$$\sum_{i=1}^{2} (1 + \tilde{\tilde{\theta}}_{jk}^{\pm}) x_{ijk}^{\pm} \geq \widetilde{\overline{WG}}_{jk}^{\pm}(t)^{(p_i)} \quad \forall j, k \tag{22b}$$

(2) Landfill capacity constraint

$$1,825 \sum_{j=1}^{3} \sum_{k=1}^{3} (x_{1jk}^{\pm} + x_{2jk}^{\pm} FE^{\pm}) \leq TL^{\pm} \tag{22c}$$

(3) WTE facility capacity constraints

$$\sum_{j=1}^{3} x_{2jk}^{\pm} \leq TE^{\pm} \quad \forall k \tag{22d}$$

(4) Non-negativity and technical constraints

$$x_{ijk}^{\pm} \geq 0 \quad \forall i, j, k \tag{22e}$$

where I is the index for the facilities ($i = 1$ for the landfill, and $i = 2$ for the WTE facility); J is the index for the three cities ($j = 1, 2, 3$); K is the index for the time periods ($k = 1, 2, 3$); $x_{ijk}^{\pm}$ is the waste flow rate from city j to facility i in period k (ton/day); $TR_{ijk}^{\pm}$ is the transportation cost from city j to facility i during period k ($/ton); $OP_{ik}^{\pm}$ is the operating cost of facility i in period k ($/ton); $FE^{\pm}$ is the residue flow from the WTE facility to the landfill (% of incoming mass to WTE facility); $FT_k^{\pm}$ is the transportation cost of waste flow from the WTE facility to the landfill in period k ($/ton); $RE_k^{\pm}$ is the revenue from the WTE facility in period k ($/ton); $\tilde{\tilde{\theta}}_{jk}^{\pm}$ is the waste collection factor for city j in period k; $\widetilde{\overline{WG}}_{jk}^{\pm}(t)^{(p_i)}$ is the waste generation rate in city j during period k with the probability of violating constraint (20b) being equal to p_i (ton/day); $TL^{\pm}$ is the capacity of the landfill (ton); $TE^{\pm}$ is the capacity of the WTE facility (ton/day).

5 Result analysis

5.1 Solutions of SI-IFSCCP

Table 5 presents the solutions obtained from the SI-IFSCCP model under a set of significance levels (p_i) including 0.01, 0.05 and 0.1. It is indicated that, the three sets of solutions under the three different p_i levels demonstrate similar waste allocation patterns. However, the specific waste-flow-allocation plans would vary with the change in p_i levels due to the temporal and spatial variations of waste management conditions.

Table 5 Solutions of the SI-IFSCCP and IFSP models

Waste flow (ton/day)	IFSP model	SI-IFSCCP model under different p_i values		
		$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$
$X_{111}^{\pm}$	[201, 268]	[197, 264]	[187, 251]	[177, 241]
$X_{112}^{\pm}$	[0, 75]	[0, 74]	[0, 70]	[0, 69]
$X_{113}^{\pm}$	[0, 83]	[0, 83]	[0, 78]	[0, 77]
$X_{121}^{\pm}$	[133, 197]	[129, 193]	[103, 161]	[93, 151]
$X_{122}^{\pm}$	[156, 221]	[151, 217]	[125, 186]	[115, 176]
$X_{123}^{\pm}$	[182, 252]	[178, 247]	[151, 216]	[140, 205]
$X_{131}^{\pm}$	[194, 260]	[190, 256]	[181, 242]	[171, 233]
$X_{132}^{\pm}$	[199, 265]	[195, 261]	[185, 248]	[176, 238]
$X_{133}^{\pm}$	[0, 72]	[0, 72]	[0, 68]	[0, 67]
$X_{211}^{\pm}$	[0, 0]	[0, 0]	[0, 0]	[0, 0]
$X_{212}^{\pm}$	[249, 249]	[245, 245]	[236, 236]	[226, 226]
$X_{213}^{\pm}$	[302, 302]	[298, 298]	[288, 288]	[278, 278]
$X_{221}^{\pm}$	[0, 0]	[0, 0]	[0, 0]	[0, 0]
$X_{222}^{\pm}$	[0, 0]	[0, 0]	[0, 0]	[0, 0]
$X_{223}^{\pm}$	[0, 0]	[0, 0]	[0, 0]	[0, 0]
$X_{231}^{\pm}$	[0, 0]	[0, 0]	[0, 0]	[0, 0]
$X_{232}^{\pm}$	[0, 0]	[0, 0]	[0, 0]	[0, 0]
$X_{233}^{\pm}$	[243, 243]	[240, 240]	[230, 230]	[221, 221]
$f_{\text{opt}}^{\pm}$ (\$$10^6$)	[175.37, 397.07]	[171.96, 391.00]	[159.05, 364.71]	[150.85, 350.14]

To explain waste allocation trends of the three cities, the modeling solutions obtained under $p_i = 0.01$ is analyzed below, while those under $p_i = 0.05$ and 0.1 can be similarly interpreted based on Table 5. Under a significance level of $p_i = 0.01$, over the planning horizon, waste from cities 1 and 3 would be shipped to either the landfill or the WTE facility, and city 2 would contribute all of its waste to the landfill. For city 1, all of its waste would be transported to the landfill in period 1, while no waste would be shipped to the WTE facility in this period. Thus, waste flowing from city 1 to the landfill would be [197, 264] ton/day in period 1, which indicates that 197 ton/day of the waste would be shipped to the landfill under advantageous conditions and 264 ton/day would be shipped under demanding conditions. However, with increasing waste generation rates during periods 2 and 3, the majority of the waste from city 1 (i.e., 245 and 298 ton/day in periods 2 and 3, respectively) would be transferred to the WTE facility. In comparison, only a small portion of the waste, i.e., [0, 74] and [0, 83] ton/day, would be allocated to the landfill in periods 2 and 3, respectively. This is probably because that the differences in operating costs between the landfill and WTE facility are steadily shrunk from period 1 to period 3, which makes the advantage of the WTE facility in transportation costs becomes more significant. For city 2, it would contribute all of the generated waste to the landfill over the planning horizon. This means that, the waste flowing from city 2 to the landfill would be [129, 193], [151, 217] and [178, 247] ton/day in periods 1, 2 and 3, respectively. This could be attributed to many factors, such as its vicinity to the landfill compared to the other two cities and the low operating costs of the landfill. As for city 3, all of the generated waste (i.e., [190, 256] and [195, 261] ton/day, respectively) would be shipped to the landfill in periods 1 and 2 due to the lower operating costs for landfilling. However, in period 3, the majority of the waste from this city (i.e., 240 ton/day) would be transported to the WTE facility, while the waste allocated to the landfill would be merely [0, 72] ton/day. This climb of the waste flows from city 3 to the WTE facility could be attributed to the city's vicinity to the WTE facility as well as the diminished advantage of the landfill over the WTE facility in operating costs. It is indicated by Table 5 that, the waste allocation patterns for the three cities under the other two significance levels would be similar to those under $p_i = 0.01$, while slight variations in specific waste-flow-allocation plans do exist among different p_i levels. For example, city 1 would contribute all of its waste to the landfill in period 1 under all of the three p_i levels, while the quantities of transported waste would vary with different waste management conditions associated with different p_i levels (i.e., [197, 264], [187, 251] and [177, 241] ton/day of waste would be transported from city 1 to the landfill in period 1 under a p_i level of 0.01, 0.05 and 0.1, respectively).

As presented in Table 5, under each p_i level, only the landfill would be utilized for waste disposal in period 1. This demonstrates that, in period 1, operating costs of waste-management facilities would be the dominant factor for waste flow allocation, while the impacts of transportation costs might be minor. In comparison, in periods 2 and 3, both the landfill and WTE facility would be jointly utilized for waste treatment and disposal. Compared to the allocation plans in period 1, the WTE facility would replace the landfill as the primary facility disposing the waste of city 1 in period 2; in period 3, the WTE facility would be more heavily used as the dominating treatment/disposal facility for the waste from both cities 1 and 3, whereas the landfill would merely be utilized to dispose a small portion of waste from these two cities under demanding conditions. It is well acknowledged that, landfilling is confronting with more and more objections from public due to its adverse environmental impacts (e.g., air pollution due to greenhouse gas emissions, as well as groundwater contamination attributed to landfill leachates) and the scarcity of land near urban areas. Hence, along with the rising waste generation rates over the planning horizon, the steady decline in the waste flowing to the landfill would be favored by local authorities and residents.

Table 5 also indicates that, since varied p_i levels correspond to different waste generation rates, any changes in p_i levels would yield different waste-flow-allocation plans. Figure 6 displays the relationship between p_i levels and system costs. It is denoted that, when p_i ascends, both the lower and upper bounds of system costs would be decreased, and vice versa. For example, when $p_i = 0.01$, $f_{\text{opt}}^{\pm} = \$[171.96, \; 391.00] \times 10^6$; comparatively, when $p_i = 0.05, f_{\text{opt}}^{\pm} = \$[159.05, 364.71] \times 10^6$. Since higher p_i levels correspond to optimistic waste-generation cases (i.e., lower waste generation rates), lower system costs could be obtained due to the relaxed constraints (i.e., expanded decision spaces). However, the risk of system violation would ascend with raised p_i levels, and the reliability of meeting treatment/disposal demands and environmental requirements would descend at the same time. In comparison, lower p_i levels correspond to higher waste generation rates. The increased strictness for the constraints would lead to higher system costs but lower risk of system violation. Therefore, p_i levels represent probabilities at which the constraints will be violated, and a tradeoff between economic efficiency and system risk could be reflected by the relationship between $f_{\text{opt}}^{\pm}$ and p_i.

The results also indicate that, through the SI-IFSCCP model, uncertain information could be directly communicated into the optimization process and thus generate interval solutions. Under each significance level, the solutions for the objective function and most of the non-zero decision variables are intervals, demonstrating that the related decisions might be sensitive to the uncertain modeling inputs. Unlike the deterministic solutions obtained from conventional linear programming (LP) models, these interval solutions from SI-IFSCCP would help generate a range of decision alternatives rather than a sole one. This feature would be favored by waste managers due to the increased flexibility and applicability in practical applications. Through adjusting waste flow values within the ranges of these interval solutions, a number of decision alternatives could be generated according to projected applicable conditions. Generally, lower decision variable values should be adopted under advantageous conditions (e.g., lower waste generation rate and higher available capacity); in contrast, higher decision variable values would correspond to more demanding conditions (e.g., higher waste generation rate and lower available capacity). Along with the variations in the values of decision variables ($x_{ijk}^{\pm}$), the net system cost would correspondingly change within its solution interval. In detail, lower decision

Fig. 6 Comparison of system costs under different p_i levels

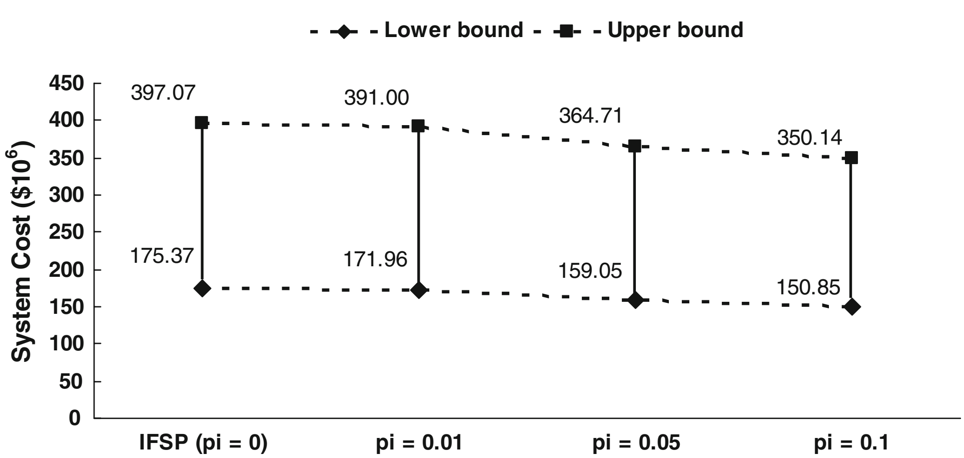

Table 6 Solutions obtained through the ICCP model

Waste flow (ton/day)	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$
X_{111}	[197, 266]	[184, 252]	[174, 242]
X_{112}	[0, 77]	[0, 76]	[0, 75]
X_{113}	[0, 86]	[0, 84]	[0, 83]
X_{121}	[131, 193]	[118, 179]	[109, 169]
X_{122}	[153, 218]	[140, 204]	[130, 194]
X_{123}	[179, 249]	[165, 234]	[155, 223]
X_{131}	[191, 257]	[178, 244]	[169, 234]
X_{132}	[195, 264]	[183, 250]	[173, 240]
X_{133}	[0, 74]	[0, 73]	[0, 72]
X_{211}	[0, 0]	[0, 0]	[0, 0]
X_{212}	[247, 247]	[233, 233]	[223, 223]
X_{213}	[301, 301]	[287, 287]	[277, 277]
X_{221}	[0, 0]	[0, 0]	[0, 0]
X_{222}	[0, 0]	[0, 0]	[0, 0]
X_{223}	[0, 0]	[0, 0]	[0, 0]
X_{231}	[0, 0]	[0, 0]	[0, 0]
X_{232}	[0, 0]	[0, 0]	[0, 0]
X_{233}	[241, 241]	[228, 228]	[218, 218]
f_{opt} ($\$10^6$)	[172.91, 394.82]	[162.05, 374.94]	[153.91, 360.03]

variable values would lead to a lower system cost, while higher decision variable values would result in a rise in system cost. Moreover, the relationship between decision makers' preferences and system-reliability levels could also be reflected by these interval solutions. Willingness to pay a higher cost would correspond to a conservative strategy, guaranteeing a higher level of system reliability. On the contrary, a strong desire to reduce costs would run into the raised risk of system instability (i.e., the risk of unforeseen conditions increases), representing an optimistic strategy. Therefore, the decisions could be adjusted within the interval solutions according to actual conditions and policy inclination, allowing waste mangers, interest partners and facility managers to incorporate implicit knowledge within the decision process and thus obtain satisfactory decision schemes.

Particularly, through the proposed SI-IFSCCP approach, decision makers' subjective judgments with the characteristics of fuzziness and two-layer randomness could be effectively addressed, avoiding over-simplification of uncertain parameters into deterministic numbers or conventional pure intervals. Various subjective judgments upon a parameter from many stakeholders with different interests and preferences could be extensively investigated and incorporated into the modeling formulation, which could guarantee a lower degree of biases during data sampling and a higher degree of public acceptance for the generated plans. Thus, the complexities in real-world MSW management problems associated with multiple uncertainties could be realistically reflected and effectively handled.

Moreover, two levels of system-violation risk could be reflected by SI-IFSCCP. The first-level risk is associated with a range of significance levels. Violations for waste-generation constraints are allowed under a set of acceptable significance levels. Within an acceptable range of p_i (i.e., admissible risk range of violating the constraints), lower p_i levels would lead to increased system reliability but decreased system efficiency (i.e., higher system cost); on the contrary, higher p_i levels would result in increased system efficiency but higher system-violation risk. This could help examine the relationship between system cost and system reliability of satisfying constraints under uncertainty. The second-level risk is related with the violations of the superiority/inferiority relationship between the constraint's left- and right-hand sides. Through applying a set of penalty costs, the economic penalties for violating waste-generation constraints could be quantified. Under an acceptable p_i level, since satisfactory waste flow plans are identified with the comprehensive considerations over potential economic penalties caused by any variations in fuzziness

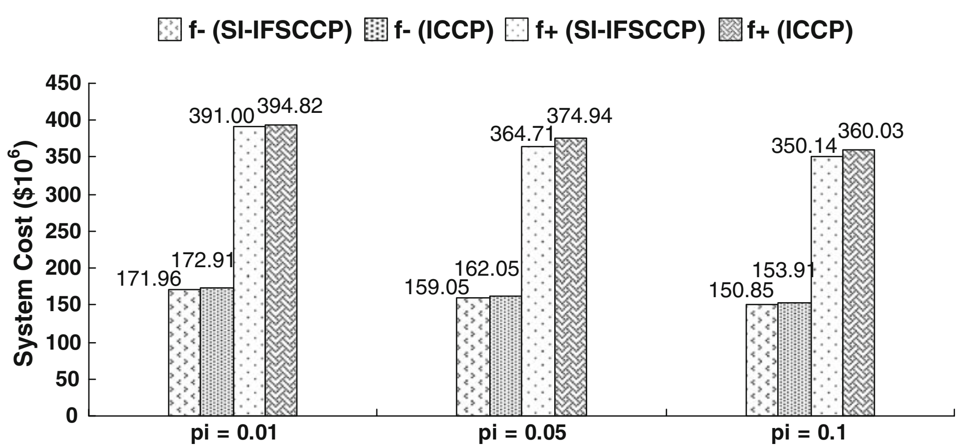

Fig. 7 Comparison of system costs between SI-IFSCCP and ICCP

Table 7 Solutions obtained through the FSCCP model

Waste flow (ton/day)	$p_i = 0.01$	$p_i = 0.05$	$p_i = 0.1$
x_{111}	229	216	206
x_{112}	0	0	0
x_{113}	337	323	313
x_{121}	159	146	136
x_{122}	184	170	160
x_{123}	212	198	188
x_{131}	222	209	200
x_{132}	227	214	205
x_{133}	274	261	251
x_{211}	0	0	0
x_{212}	281	268	257
x_{213}	0	0	0
x_{221}	0	0	0
x_{222}	0	0	0
x_{223}	0	0	0
x_{231}	0	0	0
x_{232}	0	0	0
x_{233}	0	0	0
f_{opt} (\$$10^6$)	260.23	245.87	235.01

and randomness, system robustness could be highly enhanced.

In general, SI-IFSCCP exhibits the following strengths: (a) it is capable of addressing probability distributions of fuzzy random variables (i.e., fuzzy sets with two-layer randomness), and thus various subjective judgments of many decision makers and stakeholders could be directly communicated into the optimization process, leading to a more realistic reflection of real-world MSW management problems; (b) it could reflect the two-level risk of system violation, supporting in-depth analyses of the relationship between system cost and system reliability; (c) since it does not generate complicated intermediate models and onerous variables, its computational efficiency is significantly improved compared to conventional fuzzy mathematical programming methods (e.g., robust programming), making it applicable to practical problems. The case study also suggests that, useful solutions could be obtained from SI-IFSCCP. A range of decision alternatives could be generated through adjusting the decision variable values within their interval solutions. These alternatives could allow decision makers to single out satisfactory waste flow plans according to projected system conditions and varied policy preferences, such that the flexibility and applicability could be improved. In addition, these alternatives could help gain in-depth analyses for the tradeoff between system optimality and reliability.

5.2 Comparison of SI-IFSCCP with IFSP, ICCP and FSCCP

If the lower and upper bounds of the waste generation rate of city i in period k are simplified into only one set of fuzzy random variables, the study case would then turn into an interval-parameter fuzzy-stochastic programming (IFSP) problem. The solutions obtained from the IFSP model are presented in Table 5. Since $\tilde{b}^{\pm}_{\underset{\sim}{s}}(t)$ is substituted by a fuzzy-random boundary interval $(\tilde{b}^{\pm}_{s})$, IFSP has several shortcomings compared to SI-IFSCCP. Firstly, IFSP can only generate one set of interval solutions without information about the risk of violating the waste generation constraints. For example, in IFSP, the solution for the waste flow from city 3 to the landfill in period 2 (x_{132}) is [199, 265] ton/day; comparatively, in SI-IFSCCP, they are [195, 261], [185, 248] and [176, 238] ton/day under the p_i levels of 0.01, 0.05 and 0.1, respectively. Secondly, since no relaxation on waste generation rates is allowed in IFSP, the system cost from IFSP is higher than those obtained from the SI-IFSCCP method under a range of p_i levels. As illustrated in Fig. 6, IFSP provides two extremes for the expected system costs (i.e., $f^{\pm}_{\text{opt}} = \$[175.37, 397.07] \times 10^6$), and thus may result in wasted resources. Generally, without the chance constraints,

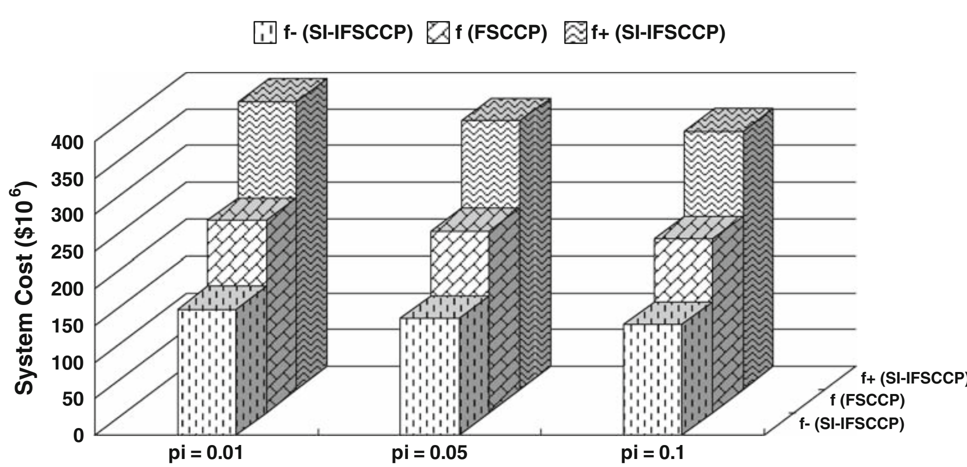

Fig. 8 Comparison of system cost between SI-IFSCCP and FSCCP

the IFSP model is unable to support in-depth analyses for the tradeoff between system cost and system violation risk.

The problem can also be solved through a conventional inexact chance-constrained linear programming (ICCP) model by substituting the fuzzy-random boundaries of intervals in left- and right-hand sides of SI-IFSCCP with deterministic values. In ICCP, the fuzzy-random lower and upper bounds of the FRBI (i.e., fuzzy-random boundary intervals) coefficients are generally replaced by the values with the highest probability (i.e., 60%) and highest membership grade (i.e., 1), representing only one of the numerous potential alternatives (based on the information of probability levels and confidence grades). Thus, ICCP is unable to reflect various subjective judgments from a number of decision makers that are presented as fuzzy random variables, leading to the losses of significant uncertain information. Consequently, as shown in Table 6 and Fig. 7, the system costs of ICCP under all p_i levels are higher than those of the SI-IFSCCP solutions.

Letting all of the coefficients that are expressed as intervals (including pure intervals, fuzzy-random boundary intervals, and intervals with fuzziness and two-layer randomness at their bounds) in SI-IFSCCP be equal to their mid-values, this problem would be converted into a fuzzy-stochastic chance-constrained linear programming (FSCCP) method. The solutions from FSCCP are provided in Table 7. As illustrated by Fig. 8, the system costs from the FSCCP solutions lie within the SI-IFSCCP solution intervals, demonstrating the stability of the SI-IFSCCP solutions. Within FSCCP, only one set of deterministic solutions corresponding to each p_i level is generated, since the model's cost coefficients (c_j) and left-/right-hand side coefficients (a_{ij} and b_i) are assumed to be deterministic numbers or fuzzy random variables. Therefore, compared with FSCCP, the SI-IFSCCP method can incorporate more uncertain information within its modeling framework. The obtained interval solutions under different risk levels of violating the waste-generation constraints can be used to generate decision alternatives and help MSW managers identify desired policies under various environmental, economic and system-reliability constraints.

6 Conclusions

In this study, a superiority-inferiority-based inexact fuzzy-stochastic chance-constrained programming (SI-IFSCCP) approach has been developed for supporting long-term municipal solid waste management under uncertainty. Through SI-IFSCCP, multiple uncertainties expressed as intervals, possibilistic and probabilistic distributions, as well as their combinations, could be directly communicated into the optimization process, avoiding over-simplification of real-world problems. Various subjective judgments of many decision makers and stakeholders with different interests and preferences could be extensively reflected, guaranteeing a lower degree of biases during data sampling and a higher degree of public acceptance for the generated plans. In addition, SI-IFSCCP has an advantage in computational efficiency as its solution method does not lead to complicated intermediate models.

The developed SI-IFSCCP method has been applied to a long-term municipal solid waste management problem to demonstrate its applicability. Useful interval solutions have been obtained. These solutions can help generate a range of decision alternatives within their interval ranges, which is favorable for decision makers due to the increased flexibility and applicability. Satisfactory waste flow plans could be identified according to policy inclination and system conditions, facilitating in-depth tradeoff analyses between system optimality and reliability. Moreover, two levels of system-violation risk could be reflected by SI-IFSCCP. Varied significance levels correspond to different risk levels of constraint violation, reflecting the relationship between economic efficiency and system reliability; under each significance level, since satisfactory waste flow plans are identified with comprehensive considerations over potential penalties caused by constraint violations, system robustness could be highly enhanced. As the first attempt for planning waste management systems through the developed SI-IFSCCP approach, the case study also suggests that this inexact optimization technique be applicable to many other environmental problems that involve multiple uncertainties, such as the problems of water resources management and air quality management.

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