A Fuzzy Robust Optimization Model for Waste Allocation Planning Under Uncertainty

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Abstract

In this study, a fuzzy robust optimization (FRO) model was developed for supporting municipal solid waste management under uncertainty. The Development Zone of the City of Dalian, China, was used as a study case for demonstration. Comparing with traditional fuzzy models, the FRO model made improvement by considering the minimization of the weighted summation among the expected objective values, the differences between two extreme possible objective values, and the penalty of the constraints violation as the objective function, instead of relying purely on the minimization of expected value. Such an improvement leads to enhanced system reliability and the model becomes especially useful when multiple types of uncertainties and complexities are involved in the management system. Through a case study, the applicability of the FRO model was successfully demonstrated. Solutions under three future planning scenarios were provided by the FRO model, including (1) priority on economic development, (2) priority on environmental protection, and (3) balanced consideration for both. The balanced scenario solution was recommended for decision makers, since it respected both system economy and reliability. The model proved valuable in providing a comprehensive profile about the studied system and helping decision makers gain an in-depth insight into system complexity and select cost-effective management strategies.

Key words: Dalian development zone; fuzzy robust optimization; robustness; trade-off; waste management

Introduction

OVER THE PAST FEW DECADES, the amount of municipal solid waste (MSW) generated annually in China remains a rapid growth due to overwhelming urbanization and socioeconomic development, leading to a major challenge for the local authority and administrative department (Xi *et al.*, 2008). For example, the waste amount delivered in China was about 0.031 million tons in 1980; this number reached to more than 0.156 million tons by 2005 and it will keep increasing in the future. Conversely, the waste disposal capacities (including landfill, incinerator, and composting plant) were decreased due to the shortage of land resources and irrationality of the waste-flow allocation pattern. The contradiction between increased waste-generation amounts and shrinking facility-treated capacities leads to many untreated

wastes, which caused a series of severe environmental pollution problems and the difficulties in generating rational management schemes. In addition, many uncertain components and interactive processes were involved in the MSW management system; these complexities and uncertainties could be multiplied by dynamic features of the management system. This may exacerbate the difficulties in the decision-making process. Therefore, how to incorporate the uncertainties and complexities within a management framework and generate decisions with sound economic and environmental efficiencies are critical to effectively manage the MSW (Huang *et al.*, 1993).

Due to the prescribed complexities and uncertainties, there were many inexact optimization methods developed for dealing with MSW management problems. The majority of these methods were related to the stochastic mathematical programming (SMP), fuzzy mathematical programming (FMP), and interval linear programming (ILP) (Chang and Wang 1997; Zou *et al.*, 2000; Cai *et al.*, 2007; Nie *et al.*, 2007; Jin *et al.*, 2013; Huang *et al.*, 1992, 1993, 1994; Xu *et al.*, 2009, 2010, 2012). Based on literature review (provided in the next section), the optimization techniques related

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to FMP were suitable in handling fuzzy uncertain parameters associated with the MSW management system and generating the cost-effective decision schemes for local managers. Nevertheless, in some real-world applications, the stability and reliability of the management patterns are equally important with its economy to realize the system balance. Especially, they attracted more attention when many types of uncertain factors and interactive processes are involved in the MSW management system. The reason lies that, the misunderstanding and inaccurate estimation for some parameters are frequently appearing in such a complex system, which could result in the infeasibility and unreliability of management alternatives, even in system failure. Because the existing FMP approaches only consider the minimized system cost as the objective function and tend to ignore the system feasibility and reliability, it is thus desired that a novel FMP approach is developed.

The major goal of this study is to develop a fuzzy robust optimization (FRO) model for supporting real-case MSW management. It is an improved FMP approach for handling fuzzy uncertainties, controlling risks of model unreliability derived by system uncertainties and complexities, as well as generating different solutions with robust characteristics. The article will be organized as follows: (1) the FRO model formulation and solution will be introduced first in the "Methodology" section; (2) the MSW management system of the study case will be introduced and a specific FRO model will be developed in the "Case study" section; and (3) result analysis and summary will be provided in the "Result analysis" and "Conclusion" sections.

Literature Review

Over the past few decades, a variety of inexact optimization techniques were developed to tackle uncertainties in environmental management problems, including SMP, FMP, and IMP, as well as their combinations. Among them, the optimization techniques related to FMP mainly included flexible fuzzy linear programming (Huang *et al.*, 1993), possibilistic fuzzy linear programming (Xu *et al.*, 2009b), fuzzy goal programming (Chang and Wang 1997), fuzzy robust programming (Nie *et al.*, 2007; Li *et al.*, 2008; Zhu *et al.*, 2009), and fuzzy chance-constrained programming (FCCP) (Qin *et al.*, 2010; Xu *et al.*, 2011; Xu and Qin, 2014). The applications of FMP techniques in the MSW management system were extensive. For example, Huang *et al.* (1993) developed a gray fuzzy linear programming and applied it to a hypothetical problem in the MSW management planning area. Nie *et al.* (2007) developed an interval-parameter fuzzy robust programming model for supporting solid waste management systems under uncertainty. Qin *et al.* (2010) developed a trapezoidal-shaped fuzzy chance-constrained mixed integer programming model for dealing with the MSW management problem in Foshan city, China. The previous studies demonstrated the effectiveness of many FMP techniques in MSW management. Nevertheless, based on traditional FMP approaches, the designed objective of the previous MSW management system mainly focused on the minimization of total system cost, where the feasibility and reliability of the management patterns were ignored; this may lead to the deviation of decision schemes and affect the accuracy and feasibility of generated management strategies.

Robust optimization with fuzzy parameters (i.e., FRO), first proposed by Pishvae *et al.* (2012), is an improved FMP method through incorporating the robust conception into the optimization models for generating feasible and reliable solutions to management problems. Similar to stochastic robust optimization (SRO) first proposed by Mulvey and Ruszczyński (1995) and Mulvey *et al.* (1995), the FRO model has an advantage, in that it considers the minimization of weighted summation among the expected objective values, differences between two extreme possible objective values, and penalty of constraints violation as objective function, instead of minimization of total cost like the traditional objective function. This will ensure the feasibility and stability of the schemes generated by FRO, even though many types of uncertainties and complexities are associated with the management system. Previously, SRO models were used in many real-world applications, such as power capacity expansion, air force/airline scheduling, scenario immunization for financial planning, and minimum weight structural design (Yu and Li, 2000; Leung *et al.*, 2007). Recently, the SRO model has gained its popularity in the environmental field (Watkins and McKinney, 1997; Jia and Culver, 2006; Xu *et al.*, 2009, 2013). For example, Watkins and McKinney (1997) applied SRO to evaluate trade-offs among expected cost, cost variability, and system performance and reliability in water transfer planning and groundwater quality management; Jia and Culver (2006) developed an SRO model to incorporate the uncertainty of water quality predictions and minimize pollutant load reductions given various levels of reliability with respect to the water quality standards; Xu *et al.* (2009) developed a stochastic robust fuzzy ILP model for supporting MSW management under uncertainty. As an extended version of robust optimization (designed under a fuzzy environment), the applications of FRO were mainly reported in the field of supply chain network design; its applications in the environmental management field were limited.

Therefore, as the first attempt in the related field, this study aims to develop an FRO model for supporting MSW management. The FRO model seeks a balanced objective among minimization of system cost, differences between two extreme possible objective values, and penalty of constraints violation. Moreover, the fuzzy constraints are tackled by the FCCP algorithm proposed by Liu and Iwamura (1998). The proposed FRO model will be applied to the MSW management in the Dalian Development Zone of Dalian city, China for demonstrating its feasibility and applicability.

Methodology

FRO, first proposed by Pishvae *et al.* (2012), is an improved FMP approach for handling fuzzy uncertainties, controlling risks of model unreliability derived by system uncertainties and complexities, as well as generating different solutions with robust characteristics. The concept of robust in the FRO model has two major implications: feasibility robustness and optimality robustness. The detail of robustness is provided by Pishvae *et al.* (2012). The solution algorithms of the FRO model depend on the fuzzy expected value calculation and FCCP (Heilpern 1992; Liu and Iwamura 1998). A general FMP model can be written as follows:

$$\text{Minimize } f = \tilde{C}X \quad (1a)$$

Subject to

$$AX \leq \tilde{B} \quad (1b)$$

$$DX \geq E \quad (1c)$$

$$X \geq 0 \quad (1d)$$

$$\tilde{C}, A, D \neq 0 \quad (1e)$$

where x is a vector of deterministic decision variables; A and D are the coefficient matrixes in the left-hand side of model constraints; $\tilde{B}$ and E are the boundary vectors in the right-hand side of model constraints; A , D , and E are the deterministic coefficient matrices or vectors for auxiliary constraints. $\tilde{C} = (r_{c1}, r_{c2}, r_{c3}, r_{c4})$ and $\tilde{B} = (r_{b1}, r_{b2}, r_{b3}, r_{b4})$ are expressed as trapezoidal fuzzy numbers with their membership functions being denoted as $\mu(\tilde{C})$ and $\mu(\tilde{B})$, respectively. Unlike general real numbers, fuzzy numbers have no natural order. Therefore, in this study, the expected value $EV(\tilde{C})$ defined by Heilpern (1992) is used to compare two trapezoidal fuzzy numbers, where the expected value $EV(\tilde{C})$ of $(\tilde{C})$ could be expressed as $EV(\tilde{C}) = \frac{1}{4}(r_{c1} + r_{c2} + r_{c3} + r_{c4})$.

The traditional way of solving model (1) is that, based on the fuzzy expected value calculation and FCCP, the objective function (1a) with the fuzzy coefficient is transformed to its expected value form; meanwhile, the fuzzy constraint (1b) is converted into crisp equivalents. Solutions at different confidence levels can be obtained. As mentioned in ‘‘Introduction’’ section, to minimize a single objective of the expected objective value can hardly guarantee the minimization of objective function under all conditions; this would lead to significant deviation of the generated decision alternative. Referring to Pishvaei *et al.* (2012), the FRO model is effective in overcoming such drawbacks and can be defined as follows:

$$\text{Minimize } \bar{f} + \gamma(f_{\max} - f_{\min}) + \delta[B^R(\alpha) - r_{b1}] \quad (2a)$$

Subject to

$$AX \leq B^R(\alpha) \quad (2b)$$

$$DX \geq E \quad (2c)$$

$$X \geq 0 \quad (2d)$$

$$\tilde{C}, A, D \neq 0 \quad (2e)$$

where $f_{\max}$ and $f_{\min}$ represent the possible maximum and minimum values of objective function (1a); r_{b1} represents the possible worst values of fuzzy parameter B . For model structure, the first term in the objective function (2a) is the expected value, which is used to reflect the system economy, where the term ‘‘system economy’’ is mainly used to describe the solution performance from the economical aspect. Generally, a high ‘‘system economy’’ means that the obtained solution has a low system cost or a high system benefit; conversely, a high cost or low benefit is expected under a low ‘‘system economy.’’ The second term in the objective function (2a) is the deviation between the possible maximum and

minimum values of objective function for controlling the ‘‘optimality robustness’’ of the obtained solutions, where γ represents the weight coefficient of the second term against the two other terms in (2a); the third term in the objective function (2a) denotes the difference between the worst case value of uncertain parameter and the value used in chance constraints (2b) for controlling the ‘‘feasibility robustness’’ of the generated solution, where δ is the penalty unit of possible violation of constraint (2b). The solutions at various confidence levels (α) and weight values (γ and δ) are obtained through solving model (2), which are used to reflect trade-off among average performance, optimality robustness, and feasibility robustness. The proposed FRO model is capable of handling fuzzy variables involved in objective function and constraints, satisfying fuzzy constraints at specific confidence levels, and generating a variety of solutions with robust characteristics. Figure 1 shows the general framework of the FRO model. In this study, the FRO model is coded and solved by using LINGO 12.0. The main advantage of this software platform is that it provides a user friendly interface, an easy-to-use language, and a series of valuable equations and functions for helping users in designing and describing system components and interactive relationships involved in a complex management system. The hardware setting for running LINGO in this study is listed as follows: (1) Operation System: Microsoft windows XP home edition (32 bits/SP2/DirectX 9.0c); (2) CPU: Intel core duo T2450 @ 2.00 GHz; and (3) SIMM: 4GB (HLX DDR2 667MHZ).

FIG. 1. Formulation and solution framework of fuzzy robust optimization model.

Generally, the computational time of solving an FRO model is within a few seconds. Such a relatively low computational requirement makes it possible to generate a variety of solutions under various combinations of weight coefficients and confidence levels, which are effective in evaluating the trade-off among system economy, feasibility, and reliability.

Case Study

Background

The Dalian Development Zone (DDZ) is located in the south part of the Liaodong Peninsula, the northeastern part of the Dalian City, Liaoning Province, China (as shown in Fig. 2). It includes 10 blocks (i.e., Maqiaozi, Dagushan, Haiqingdao, Wanli, Dongjiagou, Jinshitan, Desheng, Dalijia, Baosuiqu, and Dengsahe) and has a total population of 0.41 million approximately by 2009 with an annual growth rate of 8.56%. DDZ has an area of about 392 square kilometers and contains many types of enterprises. Gross domestic product (GDP) in DDZ was about 83.32 billion yuan by 2008. Similar to some economic zones in China, the rapid socioeconomic development and lack of a reasonable regional development plan have caused a series of environmental problems. Among all pollution sources, the untreated wastes are of significant concern. The total generation rate of waste in DDZ is almost 0.168 million ton by 2008. It is predicted that this number would increase continuously and reach 0.349 million ton by 2020. Conversely, the treated capacities of the existing facilities in Dalian city are decreasing. Currently, the total treated amounts of landfill in Dalian City have already reached

70% of its total capacity and it is difficult to provide an additional one. In addition, a small-scale incinerator in DDZ is operating at its full capacity. The contradiction between the increased waste amounts and decreased treated capacities leads to the accumulation of untreated wastes, leading to serious air and water pollutions. Nowadays, the pollution problem originated from wastes has become a major obstacle for socioeconomic development and people's normal life in DDZ. Therefore, how to effectively deal with such a problem is critical for sustainable development of the DDZ in the future.

The existing waste management system in DDZ mainly includes the following three parts, that is, the collection in waste-generation districts, the pretreatment in transfer stations, and the treatment in incinerator. Among them, seven transfer stations have been used, including three stations in Maqiaozi, two stations in Wanli, and two stations in Dagushan, respectively. Figure 3 shows the existing part of transfer stations. In addition, six transfer stations are under construction, including two stations in Maqiaozi, two stations in Haiqingdao, and two stations in Jinshitan and Dagushan, respectively. The designed standards for each transfer station has a capacity of [30, 60] t/d. Through pretreatment in the above transfer stations, the wastes would be transported to the landfill in Dalian City and the existing small-scale incinerator in DDZ. Although a series of regulations, policies, and treated technologies are implemented by the local authority and relational enterprises, there are still some problems to be clarified and solved: (1) the MSW management strategies are normally promulgated by the local authority

FIG. 2. The demonstration of Dalian Development Zone.

FIG. 3. Existing disposal facilities in the Dalian Development Zone.

according to their experiences and subjective judgment, which may lead to irrationality of the management schemes due to a lack of quantitative analysis and effective cooperation mechanism; (2) the parameters involved in the MSW management system are associated with extensive uncertainties. Among various uncertainty analysis methods, SMP is mainly used to tackle the uncertainties expressed as random variables with probabilistic distribution functions (PDF). In real-world applications, the parameter information is hardly sufficient to help generate its PDF. In addition, it is still difficult to solve a large-scale SMP model due to excessive computational burdens, even though the PDFs are available. ILP is another uncertainty analysis approach with low requirement of parameter information. However, ILP only considers the extreme conditions of an uncertain event and may result in the loss of valuable information. FMP uses expert opinion or public survey to define fuzzy possibility distributions and is capable of providing richer information for decision makers than ILP approaches; meanwhile, the related data requirement is much less compared with SMP; (3) referring to the traditional FMP optimization approaches, the designed objective of the MSW management system mainly focuses on the minimization of total system cost, where the feasibility and reliability of the management patterns are ignored; this may lead to the deviation of decision schemes. Therefore, how to design and generate cost-effective, stable, and reliable MSW management alternatives in DDZ under multiple complexities and uncertainties is an important problem for local decision makers. The proposed FRO model, as an improved version of FMP, is specifically suitable for tackling such an issue.

Model formulation

The management model considers three planning periods with each one consisting of 5 years. To find a way of treating the waste from the transfer stations, the administrative department has planned to build one landfill and one composting plant for cooperating with the existing incinerator. The generated wastes from 10 blocks should first be collected, transported to the transfer stations, and then allocated to the incinerator and composting plant. The role of landfill is to provide capacity for receiving the residues generated from the incinerator and composting plant, rather than treating the wastes from 10 blocks. Moreover, it is predicted that the waste-generation rate in DDZ will increase in the next 15 years. Therefore, the waste-flow allocations from various blocks to the waste treatment facilities should be managed properly in each stage to meet the rising waste disposal needs and, at the same time, keep the total treatment cost as low as possible. Optimization models can be used for dealing with such a problem.

As mentioned above, the waste management system in DDZ is complicated with a variety of uncertainties, which may be associated with many factors, such as waste-generation rate, unit transportation and operational cost, and treated capacities. For example, the transportation and operational cost of three facilities are normally affected by many factors, such as technology type, traffic condition, and local economical situation. It is assumed that they are expressed as trapezoidal fuzzy numbers based on site survey and statistical analysis. Table 1 shows the related parameters. Moreover, the estimation of waste-generation rates is involved in some factors,

TABLE 1. TRANSPORTATION AND OPERATIONAL COSTS PRESENTED AS FUZZY PARAMETERS

Facilities	Type	Costs and benefits (RMB)		
		k=1	k=2	k=3
Landfill	TC	*(0.71, 0.83, 1, 1.16)	(0.84, 0.99, 1.12, 1.39)	(1.03, 1.21, 1.45, 1.69)
	OC	(31.45, 37, 44.4, 51.8)	(34, 40, 48, 56)	(37.4, 44, 52.8, 61.6)
	OB	(8.5, 10, 12, 14)	(10.2, 12, 14.4, 16.8)	(12.33, 14.5, 17.4, 20.3)
Incinerator	TC	(0.71, 0.83, 1, 1.16)	(0.84, 0.99, 1.12, 1.39)	(1.03, 1.21, 1.45, 1.69)
	OC	(76.5, 90, 108, 126)	(81.6, 96, 115.2, 134.4)	(87.55, 103, 123.6, 144.2)
	OB	(59.5, 70, 85, 98)	(63.75, 75, 90, 105)	(68.85, 81, 97, 113.4)
Composting plant	TC	(0.71, 0.83, 1, 1.16)	(0.84, 0.99, 1.12, 1.39)	(1.03, 1.21, 1.45, 1.69)
	OC	(46.75, 55, 66, 77)	(51, 60, 72, 84)	(56.95, 67, 80.4, 93.8)
	OB	(11.05, 13, 15.6, 18.2)	(12.75, 15, 18, 21)	(15.3, 18, 21.6, 25.2)
Transfer station	TC	(0.71, 0.83, 1, 1.16)	(0.84, 0.99, 1.12, 1.39)	(1.03, 1.21, 1.45, 1.69)
	OC	(17, 20, 24, 28)	(21.25, 25, 30, 35)	(26.35, 31, 37.2, 43.4)

*(a, b, c, d) represents a trapezoidal-shape fuzzy set with a, b, c, and d being the four sequential parameters from left to right.
TC, transportation cost; OC, operational cost; OB, operational benefit.

such as the population amounts, GDP value, and enterprise output, and thus subjected to human judgment. The trapezoidal fuzzy numbers are used to describe the uncertain characteristics associated with the generation rates. Table 2 provides the parameters. In addition, the system parameters associated with the facilities (including existing capacities, designed capacities, and costs of various expansion or construction option) are also influenced by many factors, such as service time of equipment, quality of facility maintenance, and operation manner of workers, and thus could better be represented by fuzzy sets. The detailed information is shown in Table 3. For other variables, such as the transportation distances among blocks, transfer stations, and facilities, the residue amounts generated from two facilities have small variations and are assumed fixed values. Table 4 provides the related data.

For a MSW management system, decision makers are mainly responsible for identifying system structure and components, determining system parameters, designing rational treated facilities, allocating generated wastes from various districts to transfer stations and facilities, and reducing their threats on the surrounding communities at a low-cost context. Meanwhile, due to existence of many types of uncertainties and complexities, the system feasibility and reliability should also be taken into consideration. The proposed FRO model is suitable in tackling such a problem. First, a general FMP

model for the MSW management system in DDZ can be formulated as follows:

$$\begin{aligned}
 \text{Min } f = & \sum_{j=1}^J \sum_{i=1}^I \sum_{k=1}^K LE_k XI_{jik} (DI_{ji} T\tilde{R}_k + T\tilde{S}_k + O\tilde{I}_{ik}) \\
 & + \sum_{j=1}^J \sum_{c=1}^C \sum_{k=1}^K LE_k XC_{jck} (DC_{jc} T\tilde{R}_k + T\tilde{S}_k + O\tilde{C}_{ck}) \\
 & + \sum_{i=1}^I \sum_{l=1}^L \sum_{k=1}^K LE_k YI_{ilk} (DRI_{il} T\tilde{R}_k + O\tilde{L}_{lk} - R\tilde{L}_{lk}) \\
 & + \sum_{c=1}^C \sum_{l=1}^L \sum_{k=1}^K LE_k YC_{clk} (DRC_{cl} T\tilde{R}_k + O\tilde{L}_{lk} - R\tilde{L}_{lk}) \\
 & + \sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K E\tilde{L}_{luk} BU_{luk} + \sum_{i=1}^I \sum_{v=1}^V \sum_{k=1}^K E\tilde{I}_{ivk} BV_{ivk} \\
 & + \sum_{c=1}^C \sum_{w=1}^W \sum_{k=1}^K E\tilde{C}_{cwk} BW_{cwk} \\
 & - \sum_{j=1}^J \sum_{i=1}^I \sum_{k=1}^K LE_k XI_{jik} R\tilde{I}_{ik} - \sum_{j=1}^J \sum_{c=1}^C \sum_{k=1}^K LE_k XC_{jck} R\tilde{C}_{ck}
 \end{aligned} \tag{3a}$$

TABLE 2. WASTE-GENERATION RATES FOR EIGHT BLOCKS PRESENTED AS FUZZY PARAMETERS

Blocks	Waste-generation rate (t/d)		
	k=1	k=2	k=3
Maqiaozi	*(535.5, 630, 756, 882)	(681.615, 801.9, 962.28, 1122.66)	(841.5, 990, 1188, 1386)
Dagushan	(136.17, 160.2, 192.24, 224.28)	(258.06, 303.6, 364.32, 425.04)	(383.265, 450.9, 541.08, 631.26)
Haiqingdao	(147.9, 174, 208.8, 243.6)	(194.82, 229.2, 275.04, 320.88)	(242.25, 285, 342, 399)
Wanli	(229.5, 270, 324, 378)	(323.85, 381, 457.2, 533.4)	(420.75, 495, 594, 693)
Dongjiagou	(63.75, 75, 90, 105)	(158.1, 186, 223.2, 260.4)	(255, 300, 360, 420)
Jinshitan	(63.75, 75, 90, 105)	(153, 180, 216, 252)	(234.6, 276, 331.2, 386.4)
Desheng	(20.145, 23.7, 28.44, 33.18)	(30.09, 35.4, 42.48, 49.56)	(41.31, 48.6, 58.32, 68.04)
Dalijia	(22.95, 27, 32.4, 37.8)	(32.385, 38.1, 45.72, 53.34)	(43.35, 51, 61.2, 71.4)
Baosuiqu	(76.5, 90, 108, 126)	(109.65, 129, 154.8, 180.6)	(140.25, 165, 198, 231)
Dengsahe	(8.925, 10.5, 12.6, 14.7)	(14.79, 17.4, 20.88, 24.36)	(20.91, 24.6, 29.52, 34.44)

*(a, b, c, d) represents a trapezoidal-shape fuzzy set with a, b, c, and d being the four sequential parameters from left to right.

TABLE 3. CAPACITY EXPANSION OR CONSTRUCTION OPTIONS AND COSTS FOR WASTE MANAGEMENT FACILITIES

Facilities	Option	Capacity (t/d)	Expansion or construction cost ($\times 10^4$ RMB)		
			k=1	k=2	k=3
Landfill	1	*(340, 400, 480, 560)	(11.9, 14, 16.8, 19.6)	(10.2, 12, 14.4, 16.8)	(8.08, 9.5, 11.4, 13.3)
	2	(510, 600, 720, 840)	(13.6, 16, 19.2, 22.4)	(11.9, 14, 16.8, 19.6)	(9.78, 11.5, 13.8, 16.1)
	3	(680, 800, 960, 1120)	(16.15, 19, 22.8, 26.6)	(14.45, 17, 20.4, 23.8)	(12.33, 14.5, 17.4, 20.3)
Incinerator	1	(170, 200, 240, 280)	(102, 120, 144, 168)	(85, 100, 120, 140)	(63.75, 75, 90, 105)
	2	(255, 300, 360, 420)	(119, 140, 168, 196)	(102, 120, 144, 168)	(85, 100, 120, 140)
	3	(340, 400, 480, 560)	(144.5, 170, 204, 238)	(127.5, 150, 180, 210)	(110.5, 130, 156, 182)
Composting plant	1	(468, 550, 660, 770)	(425, 500, 600, 700)	(255, 300, 360, 420)	(102, 120, 144, 168)
	2	(587, 690, 828, 966)	(680, 800, 960, 1100)	(425, 500, 600, 700)	(178.5, 210, 252, 294)
	3	(706, 830, 996, 1162)	(1020, 1200, 1440, 1700)	(680, 800, 960, 1100)	(306, 360, 432, 504)

*(a, b, c, d) represents a trapezoidal-shape fuzzy set with a, b, c, and d being the four sequential parameters from left to right.

Subject to

(i) Constraints of treatment/disposal capacity:

$$\sum_{k=1}^K LE_k \left(\sum_{i=1}^I \sum_{l=1}^L YI_{ilk} + \sum_{c=1}^C \sum_{l=1}^L YC_{clk} \right) \leq \sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K \Delta C \tilde{L}_{luk} BU_{luk}, \quad (3b)$$

$$\sum_{j=1}^J \sum_{i=1}^I XI_{jik} \leq \sum_{i=1}^I CA \tilde{I}_i + \sum_{i=1}^I \sum_{v=1}^V \sum_{k'=1}^k \Delta C \tilde{I}_{ivk'} BV_{ivk'}, \quad \forall k, \quad (3c)$$

$$\sum_{j=1}^J \sum_{c=1}^C XC_{jck} \leq \sum_{c=1}^C \sum_{w=1}^W \sum_{k'=1}^k \Delta C \tilde{C}_{cwk'} BW_{cwk'}, \quad \forall k, \quad (3d)$$

(ii) Capacity constraints for transfer stations:

$$\sum_{i=1}^I XI_{jik} + \sum_{c=1}^C XC_{jck} \geq G \tilde{W}_{jk}, \quad \forall j, k, \quad (3e)$$

$$\begin{aligned} & \sum_{j=1}^J \sum_{i=1}^I XI_{jik} + \sum_{j=1}^J \sum_{c=1}^C XC_{jck} + \sum_{i=1}^I \sum_{l=1}^L YI_{ilk} \\ & + \sum_{c=1}^C \sum_{l=1}^L YC_{clk} \leq MT \tilde{C}_k, \quad \forall k, \end{aligned} \quad (3f)$$

(iii) Mass balance equations:

$$\sum_{l=1}^L YI_{ilk} = \sum_{j=1}^J XI_{jik} FI_k, \quad \forall i, k, \quad (3g)$$

$$\sum_{l=1}^L YC_{clk} = \sum_{j=1}^J XC_{jck} FC_k, \quad \forall c, k, \quad (3h)$$

(iv) Constraints of capacity expansion options:

$$\begin{aligned} 0 & \leq \sum_{u=1}^U \sum_{k=1}^K BU_{luk} \leq 1, \quad 0 \leq \sum_{v=1}^V BV_{ivk} \leq 1, \\ 0 & \leq \sum_{w=1}^W \sum_{k=1}^K BW_{cwk} \leq 1, \quad \forall l, u, i, v, c, w, k, \end{aligned} \quad (3i)$$

BU_{luk} , BU_{ivk} , and BU_{cwk} are integers;

(v) Non-negativity constraints:

$$XI_{jik} \geq 0, \quad XC_{jck} \geq 0, \quad \forall i, j, c, l, k, \quad (3j)$$

TABLE 4. DISTANCES AMONG BLOCKS, TRANSFER STATIONS, AND FACILITIES

Blocks	Distances (km)		
	Landfill	Incinerator	Composting plant
Maqiaozi	28	22	31
Dagushan	30	35	33
Haiqingdao	28	30	31
Wanli	27	23	26
Dongjiagou	21	27	19
Jinshitan	22	38	18
Desheng	17	32	13
Dalijia	15	40	12
Baosuiqu	28	31	26
Dengsahe	29	43	17

where f is net system cost (\$); k is index of time periods where K is number of time periods; LE_k is length of time period k (d); l , i , and c are indexes of specific landfills, incinerators, and composting plants, respectively; j is index of transfer stations; u is index of construction options for landfills; v is index of expansion options for incinerators; w is index of construction options for composting plants; XI_{jik} and XC_{jck} are decision variables representing waste flows from transfer station j to incinerator i and composting plant c (t/d), respectively; YI_{ilk} and YC_{clk} are decision variables representing residue flows from incinerator i and composting plant c to landfill l (t/d), respectively; BU_{luk} , BV_{ivk} , BW_{cwk} are binary decision variables for landfill l , incinerator i , and composting plant c , respectively; CAI_i is the existing capacities of

incinerator i (t/d); ΔCL_{luk} , ΔCI_{ivk} , and ΔCC_{cwk} are capacity construction amounts for landfill l and composting plant c , capacity expansion amounts for incinerator i (t/d), respectively; DI_{ji} and DC_{jc} are the distances from transfer station j to incinerator i and composting plant c (km), respectively; DRI_{il} and DRC_{cl} are transportation distances from incinerator i and composting plant c to landfill l (km), respectively; EL_{luk} , EI_{ivk} , EC_{cwk} are unit expansion or construction costs for landfill l , incinerator i , and composting plant c (\$/t), respectively; FI_k and FC_k are residue rates from incinerator and composting plant to landfill (%), respectively; GW_{jk} is waste amount generated in various blocks covered by transfer station j (t/d); MTC_k is the maximum transportation capacity (t/d); OL_{lk} , OI_{ik} , and OC_{ck} are unit operational costs for landfill l , incinerator i , and composting plant c (\$/t), respectively; RL_{lk} , RI_{ik} , and RC_{ck} are unit revenues for landfill l , incinerator i , and composting plant c (\$/t), respectively; TR_k is unit transportation cost (\$/t·km); TS_k is unit operational cost for transfer stations (\$/t). The definitions and explanations of fuzzy parameters are referring to model (1). Based on the general FRO model in the “Methodology section,” an FRO model for the MSW management system in DDZ can be formulated as follows (Pishvaei *et al.*, 2012):

$$\sum_{i=1}^I XI_{jik} + \sum_{c=1}^C XC_{jck} \geq G\tilde{W}_{jk}^L(\alpha_l) \quad \forall j, k, \quad (4e)$$

$$\sum_j \sum_{i=1}^I XI_{jik} + \sum_j \sum_{c=1}^C XC_{jck} + \sum_{i=1}^I \sum_{l=1}^L YI_{ilk} + \sum_{c=1}^C \sum_{l=1}^L YC_{clk} \leq MTC_k^R(\alpha_l) \quad \forall k \quad (4f)$$

$$\sum_{l=1}^L YI_{ilk} = \sum_{j=1}^J XI_{jik} FI_k, \quad \forall i, k, \quad (4g)$$

$$\sum_{l=1}^L YC_{clk} = \sum_{j=1}^J XC_{jck} FC_k, \quad \forall c, k, \quad (4h)$$

$$0 \leq \sum_{u=1}^U \sum_{k=1}^K BU_{luk} \leq 1, \quad 0 \leq \sum_{v=1}^V BV_{ivk} \leq 1, \quad 0 \leq \sum_{w=1}^W \sum_{k=1}^K BW_{cwk} \leq 1, \quad \forall l, u, i, v, c, w, k, \quad (4i)$$

$$\begin{aligned} \text{Min } h = & E[f] + \beta(f_{\max} - f_{\min}) + \gamma_1 \left[\sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K \Delta C\tilde{L}_{luk}^R(\alpha_l) - \sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K \Delta CL_{luk}^1 \right] BU_{luk} \\ & + \gamma_2 \left[\sum_{i=1}^I CAI_i^R(\alpha_l) - \sum_{i=1}^I CAI_i^1 + \sum_{i=1}^I \sum_{v=1}^V \sum_{k=1}^k \Delta CI_{ivk'}^R(\alpha_l) BV_{ivk'} - \sum_{i=1}^I \sum_{v=1}^V \sum_{k=1}^k \Delta CI_{ivk'}^1 BV_{ivk'} \right] \\ & + \gamma_3 \left[GW_{jk}^4 - G\tilde{W}_{jk}^L(\alpha_l) \right] + \gamma_4 \left[\sum_{c=1}^C \sum_{w=1}^W \sum_{k=1}^k \Delta C\tilde{C}_{cwk'}^R(\alpha_l) - \sum_{c=1}^C \sum_{w=1}^W \sum_{k=1}^k \Delta CC_{cwk'}^1 \right] BW_{cwk'} \\ & + \gamma_5 \left[\sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K \Delta C\tilde{L}_{luk}^R(\alpha_l) - \sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K \Delta CL_{luk}^1 \right] BU_{luk} + \gamma_6 \left[MTC_k^R(\alpha_l) - MTC_k^1 \right] \end{aligned} \quad (4a)$$

Subject to

$$\begin{aligned} \sum_{k=1}^K LE_k \left(\sum_{i=1}^I \sum_{l=1}^L YI_{ilk} + \sum_{c=1}^C \sum_{l=1}^L YC_{clk} \right) \\ \leq \sum_{l=1}^L \sum_{u=1}^U \sum_{k=1}^K \Delta C\tilde{L}_{luk}^R(\alpha_l) BU_{luk} \end{aligned} \quad (4b)$$

$$\begin{aligned} \sum_{j=1}^J \sum_{i=1}^I XI_{jik} \leq \sum_{i=1}^I CAI_i^R(\alpha_l) \\ + \sum_{i=1}^I \sum_{v=1}^V \sum_{k=1}^k \Delta CI_{ivk'}^R(\alpha_l) BV_{ivk'} \quad \forall k \end{aligned} \quad (4c)$$

$$\sum_{j=1}^J \sum_{c=1}^C XC_{jck} \leq \sum_{c=1}^C \sum_{w=1}^W \sum_{k=1}^k \Delta C\tilde{C}_{cwk'}^R(\alpha_l) BW_{cwk'} \quad \forall k \quad (4d)$$

BU_{luk} , BV_{ivk} , and BW_{cwk} are integers;

$$XI_{jik} \geq 0, \quad XC_{jck} \geq 0, \quad \forall i, j, c, l, k; \quad (4j)$$

The solutions (including the expected objective $\bar{f}_{opt}$, the general decision variables x_{opt} , and binary decision variables B_{opt}) at various α levels and weight values of γ and β are obtained by a solving model (4).

Results Analysis

Tables 5–7 demonstrate the obtained solutions under three ratios of 10^{-4} , 10^{-6} , and 10^{-8} and 9 confidence levels from 0.1 to 0.9, respectively. Considering the objective function in the FRO model is to minimize the weighted summation among the expected objective values, the differences between two extreme possible objective values, and penalty of constraints violation, the ratio is thus calculated by dividing β by γ to reflect the relative importance of the weight coefficients of γ and β . According to the obtained results under different ratios, the changing trends of objective function values and most of the decision variables under different sets

TABLE 5. SOLUTIONS FROM FRO MODEL UNDER THREE CONFIDENCE LEVELS AT A RATIO OF 10^{-4}

Facility	Municipality	Solutions from FRO model (t/d)								
Fuzzy confidence levels		0.3			0.6			0.9		
Period		k=1	k=2	k=3	k=1	k=2	k=3	k=1	k=2	k=3
Incinerator	j=1	261.98	717.70	886.05	380.88	753.79	930.60	499.77	789.87	975.15
	j=2	0	0	65.71	0	0	174.73	0	0	283.76
	j=3	0	0	255.08	0	0	267.90	0	89.32	280.73
	j=4	0	230.03	443.03	0	347.32	465.30	0	375.29	487.58
	j=5	0	0	0	0	0	0	0	0	0
	j=6	0	0	0	0	0	0	0	0	0
	j=7	0	0	0	0	0	0	0	0	0
	j=8	0	0	0	0	0	0	0	0	0
	j=9	0	0	0	0	0	0	0	0	0
	j=10	0	0	0	0	0	0	0	0	0
Composting plant	j=1	301.87	0	0	211.32	0	0	120.78	0	0
	j=2	143.38	271.72	337.85	150.59	285.38	249.11	157.80	299.05	160.38
	j=3	155.73	205.13	0	163.56	215.45	0	171.39	136.44	0
	j=4	241.65	110.96	0	253.8	10.82	0	265.95	0	0
	j=5	67.13	166.47	268.50	70.50	174.84	282.00	73.88	183.21	295.50
	j=6	67.13	161.1	247.02	70.50	169.20	259.44	73.88	177.30	271.86
	j=7	21.21	31.68	43.50	22.28	33.28	45.68	23.34	34.87	47.87
	j=8	24.17	34.10	45.65	25.38	35.81	47.94	26.60	37.53	50.24
	j=9	80.55	115.46	147.68	84.60	121.26	155.10	88.65	127.07	162.53
	j=10	9.40	15.57	22.02	9.87	16.36	23.12	10.34	17.14	24.23
Expected system cost ($\times 10^6$ RMB)		1238.27			1284.18			1331.24		

FRO, fuzzy robust optimization.

of ratio values are similar. Thus, we consider ratio values of 10^{-4} , 10^{-6} , and 10^{-8} as representatives and use them for further result analysis. In addition, the fuzzy constraints in the FRO model are allowable to be satisfied at predetermined confidence levels, where the confidence level normally is in

the range from 0.1 to 0.9 for reflecting different constraints satisfaction extents.

From Tables 5 to 7, as important components of the FRO model, the variations in the two indicators (i.e., ratio and confidence level) would result in obvious changes of solutions.

TABLE 6. SOLUTIONS FROM FRO MODEL UNDER THREE CONFIDENCE LEVELS AT A RATIO OF 10^{-6}

Facility	Municipality	Solutions from FRO model (t/d)								
Fuzzy confidence levels		0.3			0.6			0.9		
Period		k=1	k=2	k=3	k=1	k=2	k=3	k=1	k=2	k=3
Incinerator	j=1	563.85	717.70	886.05	592.20	753.79	930.60	620.55	789.87	975.15
	j=2	143.38	271.72	403.56	150.59	0.00	381.80	157.80	0.00	283.76
	j=3	155.73	205.13	255.08	163.56	168.38	267.90	171.39	89.32	280.73
	j=4	241.65	341.00	443.03	253.80	358.14	465.30	265.95	375.29	487.58
	j=5	67.13	166.47	0	70.50	0	0	73.88	0	0
	j=6	67.13	161.10	0	70.50	0	0	73.88	0	0
	j=7	21.21	31.68	0	22.28	0	0	23.34	0	0
	j=8	24.17	34.10	0	25.38	0	0	26.60	0	0
	j=9	80.55	115.46	37.35	84.60	0	0	88.65	0	0
	j=10	9.40	15.57	0	9.87	0	0	10.34	0	0
Composting plant	j=1	0	0	0	0	0	0	0	0	0
	j=2	0	0	0	0	285.38	42.04	0	299.05	160.38
	j=3	0	0	0	0	47.07	0.00	0	136.44	0.00
	j=4	0	0	0	0	0.00	0.00	0	0	0
	j=5	0	0	268.50	0	174.84	282.00	0	183.21	295.50
	j=6	0	0	247.02	0	169.20	259.44	0	177.30	271.86
	j=7	0	0	43.50	0	33.28	45.68	0	34.87	47.87
	j=8	0	0	45.65	0	35.81	47.94	0	37.53	50.24
	j=9	0	0	110.32	0	121.26	155.10	0	127.07	162.53
	j=10	0	0	22.02	0	16.36	23.12	0	17.14	24.23
Expected system cost ($\times 10^6$ RMB)		1131.01			1218.07			1289.65		

TABLE 7. SOLUTIONS FROM FRO MODEL UNDER THREE CONFIDENCE LEVELS AT A RATIO OF 10^{-8}

Facility	Municipality	Solutions from FRO model (t/d)								
Fuzzy confidence levels		0.3			0.6			0.9		
Period		k=1	k=2	k=3	k=1	k=2	k=3	k=1	k=2	k=3
Incinerator	j=1	563.85	717.70	886.05	592.20	753.79	930.60	620.55	789.87	975.15
	j=2	143.38	271.72	403.56	150.59	0.00	381.80	157.80	299.05	444.14
	j=3	155.73	205.13	255.08	163.56	168.38	267.90	171.39	225.76	280.73
	j=4	241.65	341.00	443.03	253.80	358.14	465.30	265.95	375.29	487.58
	j=5	67.13	166.47	0	70.50	0	0	73.88	183.21	0
	j=6	67.13	161.10	0	70.50	0	0	73.88	177.30	0
	j=7	21.21	31.68	0	22.28	0	0	23.34	34.87	0
	j=8	24.17	34.10	0	25.38	0	0	26.60	37.53	0
	j=9	80.55	115.46	37.35	84.60	0	0	88.65	127.07	10.42
	j=10	9.40	15.57	0	9.87	0	0	10.34	17.14	0.00
Composting plant	j=1	0	0	0	0	0	0	0	0	0.00
	j=2	0	0	0	0	285.38	42.04	0	0	0.00
	j=3	0	0	0	0	47.07	0	0	0	0.00
	j=4	0	0	0	0	0	0	0	0	0.00
	j=5	0	0	268.50	0	174.84	282.00	0	0	295.50
	j=6	0	0	247.02	0	169.20	259.44	0	0	271.86
	j=7	0	0	43.50	0	33.28	45.68	0	0	47.87
	j=8	0	0	45.65	0	35.81	47.94	0	0	50.24
	j=9	0	0	110.32	0	121.26	155.10	0	0	152.10
	j=10	0	0	22.02	0	16.36	23.12	0	0	24.23
Expected system cost ($\times 10^6$ RMB)		1131.01			1218.07			1248.17		

To analyze the influences on the obtained solutions derived by indicator variations, it is generally assumed that when one indicator is adjusting, the other indicator remains unchanged. First, under the same ratio, the obtained solutions have variations under various confidence levels. For example, under the ratio of 10^{-4} , the sum of the allocated amounts to the incinerator and composting plant would increase as the increase of confidence level, namely, 5988.48, 6092.33, 6196.17, 6300.02, 6403.87, 6507.71, 6611.56, 6715.41, and 6819.25 t/d, respectively. Among them, the total treated amounts by the incinerator would increase, namely, 2552.28, 2705.93, 2859.57, 3013.22, 3166.87, 3320.51, 3474.16, and 3781.45 t/d, respectively; conversely, the wastes allocated to the composting plant would decrease, namely, 3436.20, 3386.40, 3336.60, 3286.80, 3237.00, 3187.20, 3137.40, 3087.60, and 3037.80 t/d, respectively. This is because, according to the FCCP algorithm, the confidence level is used to represent the extent of constraints satisfaction, the increase of confidence level means the constraints in the regulated treated amounts and designed treated capacities are strict, and thus, the total treated amounts by the two facilities would increase. Moreover, the solution suggests that the two facilities could be used together to dispose the wastes; this would lead to a different variation trend. The increase of the treated amounts allocated to the incinerator is accompanied with the decrease of those treated by the composting plant. For example, under the ratio of 10^{-8} , at various confidence levels, the wastes allocated to the incinerator would be 5229.48, 5344.33, 5459.17, 5574.02, 5688.87, 4769.18, 6227.69, 6063.41, and 5977.45 t/d, respectively. Those by the composting plant would be 759.00, 748.00, 737.00, 726.00, 715.00, 855.33, 383.87, 682.00, and 841.80 t/d, respectively. To enhance the system economy, the treated amounts by the incinerator are higher than those allocated to the composting

plant, since the expansion costs of incinerator are lower than the construction cost of composting plant.

Variation trends also reflect in binary decision variables, which are used to express whether three facilities need to be expanded or constructed. Figure 4 shows the solutions of expansion or construction options under various ratios and confidence levels. As shown in Fig. 4, the expansion or construction amounts would increase as the increase of confidence level, even though the ratio is stable. For example, under a ratio of 10^{-8} , at confidence levels from 0.1 to 0.7, the landfill would be constructed at the start of period 1 with designed treated amounts of 510 t/d; at the confidence levels of 0.8 and 0.9, the designed capacities of landfill would reach 680 t/d. The same situation also happens in the incinerator and composting plant. For instance, at confidence levels of 0.1 to 0.7, the incinerator would be expanded at the start of period 1 with an increment of 255 t/d; at the confidence levels of 0.8 and 0.9, the expansion amounts would be 340 t/d. This is due to the fact that the increase of treated amounts leads to the increase of designed treated capacities.

In addition, the variation in ratio also results in the change of obtained solutions. As shown in Tables 5–7, as the increase of ratio, the difference between the allocated amounts from 10 blocks to two facilities is decreasing. For example, under a ratio of 10^{-8} , the differences at various confidence levels are 4470.48, 4596.33, 4722.17, 4848.02, 4973.87, 3030.65, 5843.82, 5351.41, and 5135.65 t/d, respectively; under a ratio of 10^{-6} , those at nine confidence levels are 4470.48, 4596.33, 4722.17, 4848.02, 2815.87, 3030.65, 5843.82, 3293.01, and 2768.85 t/d, respectively; under a ratio of 10^{-4} , those at nine confidence levels are –883.92, –680.47, –447.03, –273.58, –70.13, 133.31, 336.76, 540.21, and 743.65 t/d, respectively. This is due to the fact that the increase of ratio means that the

FIG. 4. Optimized capacity expansion or construction scheme.

minimization in deviations between two extreme possible objective values (i.e., optimality robustness) is more important; this would lead to the decrease of difference in the treated amounts allocated to the two facilities. In fact, this balanced allocation pattern is suitable in ensuring system reliability, although the system cost is also increasing. Conversely, the allocated pattern depending on the single facility may lead to the

system failure risk, although it is cost effective. This also reflects the trade-off between system economy, feasibility, and reliability. The ratio makes FRO capable of evaluating the trade-off among system economy, feasibility, and reliability and providing waste managers a spectrum of decision alternatives.

Figure 5 shows the variation trend of the expected system cost under various ratio values and confidence levels. As

FIG. 5. Total system costs under various conditions.

depicted in Fig. 5, under the same ratio, the expected value of system cost would increase as the increase of confidence level. For example, under a ratio of 10^{-4} , the system costs at confidence levels from 0.1 to 0.9 are 1207.09, 1222.24, 1238.27, 1253.47, 1268.67, 1284.18, 1299.80, 1315.13, and 1331.24 ($\times 10^6$ RMB), respectively. This is because, according to the FCCP algorithm rule, the increase of confidence level would result in strict constraints, where the treated amounts allocated to three facilities would increase and the expansion or construction options with high cost would be used (thus, the expected value of system cost would increase). Moreover, the change of ratio also has influence on the expected value of system cost. As shown in Fig. 5, the expected value would increase as the increase of ratio when the confidence level remains unchanged. The reason mainly lies that, as the increase of ratio, the importance of deviations between two extreme objective values (i.e., optimality robustness) is enhanced compared to expected objective values (i.e., system economy) and penalty of the constraints violation (i.e., feasibility robustness), leading to the decrease of difference in treated amounts allocated to two facilities. This also means that more expansion or construction amounts are required and higher expected system costs would be expected. The variation in ratio can effectively reflect the trade-off among system economy, feasibility, and reliability. This balanced allocation pattern with high system cost could decrease the deviation under extreme objective values and enhance system feasibility and reliability. Conversely, the allocated pattern depending on the single facility is effective in reducing the system cost; meanwhile, the system failure risk is also increasing.

As demonstrated before, the variations in two indicators make the FRO model capable of generating a variety of solutions under various conditions and evaluating the trade-off among system economy, feasibility, and reliability. Accordingly, the values of two indicators are predetermined by decision makers according to their preferences in accepting system failure risk. Among them, the confidence level is used to represent the extent of constraints satisfaction, the increase of confidence level means the constraints in the regulated

treated amounts and designed treated capacities are strict, and the system reliability would be enhanced. Similarly, the increase of ratio means the minimization in deviations between two extreme possible objective values (i.e., optimality robustness) is more important, such that the safety of generated allocation patterns was increased. In a practical MSW management system, if the improvement of environmental quality is preferred, then the combinations of high ratio value and confidence levels are more appropriate. Conversely, low system cost and high system failure risk are associated with low indicator values. To fully reflect the trade-off between system economy and reliability, the ranges of the two indicators should be sufficiently wide. Generally, the following three types of solutions are obtained for the decision-making process, that is, economy prior alternative under a ratio of 10^{-8} at a confidence level of 0.1, environment friendly alternative under a ratio of 10^{-4} at a confidence level of 0.9, and coordinated scheme between economy and environment under a ratio of 10^{-6} at a confidence level of 0.5, respectively. Considering DDZ is still at the stage of stable economic development and environmental quality improvement, it is thus suggested that a compromise alternative (e.g., scheme under a ratio of 10^{-6} at a confidence level of 0.5) be adopted as the decision basis for the generation of final decision alternative, which is helpful in realizing the balance between system economy and risk.

Generally, the above results demonstrate that the proposed FRO model has advantages in two aspects. In terms of methodology, it overcomes the limitations of traditional FMP methods through incorporating the minimization of the weighted summation among the expected objective values, the differences between two extreme possible objective values, and penalty of the constraints violation into the objective function, rather than the minimization of system cost. The system reliability is enhanced and it is especially useful when many types of uncertainties and complexities are involved in the MSW management system. In terms of practical application, the variation of two indicators (i.e., ratio and confidence level) has enriched solutions' diversity, where three types of solutions are obtained, including economy prior,

environment friendly, and coordinated between economy and environment, respectively. Finally, the compromise schemes are recommended as the decision basis for the decision-making process due to their robust characteristics. However, the FRO model still needs to be improved, especially in the following two aspects. First, a variety of solutions are obtained through adjusting two indicators, which are suitable in providing space to decision makers for the decision-making process. However, it may also lead to difficulties in the selection and evaluation of generated solutions. A multi-criteria decision analysis (MCDA) tool is capable of incorporating decision makers' preference of economy and risk into evaluation processes and thus could be introduced for tackling such a difficulty. Second, FRO could handle fuzzy parameters related to objective function and constraints. In fact, depending on uncertain characteristics presented by some parameters and available data quality, other different uncertainty analysis methods, such as SMP and ILP, should also be used. For example, when some parameters exhibit random characteristics and own long-term time series historical data, they can be described by PDFs. Moreover, some parameters have a small variation range and suffer from a lack of complete data, and they are more suitable to be described by discrete intervals. Therefore, other types of uncertain optimization methods could be incorporated into the FRO model for handling more complicated problems. Third, other types of optimization technologies, such as nonlinear programming (NP) and multiobjective programming (MOP), also have the potential to be incorporated with FRO for further improvements. For example, in a practical MSW management system, the operational cost of a treatment technology could exhibit the economy-of-scale feature and this may result in the formulation of a nonlinear objective function. Referring to Huang and Chen (2001) and Qin *et al.* (2010), the solution algorithms, such as linearization conversion or intelligent algorithm, are capable of solving NP models. It is desired to further explore the possibility of incorporating FRO with NP in the future. In addition, the minimization of pollutant emission amounts is also a major concern for waste managers, in addition to the economical objective. To obtain a balance among various objectives in real-world decision making, the MOP technique is desired. Previously, MOP has been integrated with some inexact optimization models and successfully applied in many environmental management problems (Chen *et al.*, 2008; Wang *et al.*, 2006). It has a strong potential to be incorporated with the proposed FRO model for handling more complicated cases. Fourth, as an extended version of the RO model from stochastic to fuzzy environment, the FRO model can effectively reflect conditions when the uncertainties in constraints can be expressed as fuzzy membership functions, where all fuzzy constraints are tackled by the FCCP algorithm without considering their differences. Nevertheless, as described by Mulvey and Ruszczyński (1995) and Mulvey *et al.* (1995), the SRO model normally includes structural and control constraints, where they are tackled by different methods. In addition, the violation variables are not incorporated into the FRO model, where the difference between the worst case value of uncertain parameters and the value used in chance constraints is considered as the scale of the constraints violation. There are some deviations with the SRO model. In fact, to incorporate the violation variables into the model for describing the

magnitude of constraints violation is an important feature of an RO model. The related topics on how to improve the FRO model deserve further investigations.

Conclusions

In this study, an FRO model was developed for supporting MSW management. The major advantage of FRO is that it considers the minimization of weighted summation among expected objective values, differences between two extreme possible objective values, and penalty of constraints violation as objective function, rather than a single objective of minimizing total system cost. This will ensure the feasibility and stability of decision schemes generated by the FRO model. Moreover, the constraints with fuzzy parameters were allowable to be satisfied at predetermined confidence levels. A variety of solutions could be obtained through adjusting the weight coefficient and confidence level, which reflected the trade-off among system economy, feasibility, and reliability.

The proposed model was applied to a real-world solid waste management case in the DDZ of Dalian City, China. The obtained results demonstrated that the proposed model was capable of generating a variety of solutions under various conditions and evaluating the trade-off between system economy and reliability. Three types of solutions were provided by the FRO model, including economy prior, environment friendly, and coordinated between economy and environment, respectively. It is suggested that the compromise alternative (e.g., scheme under a ratio of 10^{-6} at a confidence level of 0.5) should be the decision basis for the generation of final decision alternative, which was helpful in realizing the balance between system economy and risk. The successful applications of FRO in DDZ are expected to be a good demonstration for real-world solid waste management problems. In further studies, other decision support techniques, such as MCDA, SMP, and ILP, have the potential to be further integrated into the FRO model for dealing with more complex problems.

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Author Disclosure Statement

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