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Inexact fuzzy-stochastic constraint-softened programming – A case study for waste management

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ABSTRACT

In this study, an inexact fuzzy-stochastic constraint-softened programming method is developed for municipal solid waste (MSW) management under uncertainty. The developed method can deal with multiple uncertainties presented in terms of fuzzy sets, interval values and random variables. Moreover, a number of violation levels for the system constraints are allowed. This is realized through introduction of violation variables to soften system constraints, such that the model's decision space can be expanded under demanding conditions. This can help generate a range of decision alternatives under various conditions, allowing in-depth analyses of tradeoffs among economic objective, satisfaction degree, and constraint-violation risk. The developed method is applied to a case study of planning a MSW management system. The uncertain and dynamic information can be incorporated within a multi-layer scenario tree; revised decisions are permitted in each time period based on the realized values of uncertain events. Solutions associated with different satisfaction degree levels have been generated, corresponding to different constraint-violation risks. They are useful for supporting decisions of waste flow allocation and system-capacity expansion within a multistage context.

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1. Introduction

In municipal solid waste (MSW) management, uncertainties exist in related costs, impact factors and objectives, and are presented as fuzzy, probability and/or interval formats. Such uncertainties can affect the related optimization processes and the generated decision schemes (Huang et al., 1993; Yeomans et al., 2003). Consequently, various methods dealing with uncertainties have been developed for the planning of MSW management systems (Gottinger, 1986; Kirca and Erkip, 1988; Baetz, 1990; Zhu and Revelle, 1993; Jaung et al., 1995; Chanas and Zielinski, 2000; Wilson and Baetz, 2001a,b; Huang et al., 2002; Solano et al., 2002a,b; Yeomans and Huang, 2003; Zeng and Trauth, 2005; Chang et al., 2005; García et al., 2005; Li and Huang, 2006, 2007; Chang and Davila, 2007, 2008). Most of them can be grouped into fuzzy, stochastic and interval mathematical programming methods (abbreviated as FMP, SMP and IMP).

IMP can tackle uncertainties expressed as intervals that exist in the model's left- and/or right-hand sides as well as the objective function; however, it is incapable of dealing with uncertainties expressed as possibilistic and probabilistic distributions (Huang et al., 1993). FMP considers uncertainties as fuzzy sets, and is effective in reflecting ambiguity and vagueness in resource availabilities. Combining advantages of FMP and IMP, interval-fuzzy mathematical programming (IFMP) methods were developed for tackling uncertainties presented as interval values and fuzzy sets (Huang et al., 1993, 1995; Chang et al., 1997). However, IFMP could become infeasible when the constraints were strict under demanding conditions. Recently, Huang et al. (2002) introduced a regret analysis approach to relax the constraints of IFMP (Burn and Barbara, 1992; Ellis and Bowman, 1994), such that the IFMP model's decision space could be expanded through introducing a number of violation variables for the constraints. However, the constraint-relaxed IFMP had difficulty in dealing with uncertainties expressed as random variables; furthermore, it was lack of linkage to economic consequences of violated policies as pre-regulated by authorities since recourse actions were not considered to correct any infeasibilities.

Stochastic programming with recourse was effective for problems where an analysis of policy scenarios is desired and coefficients are random with known probability distributions. In this method, decision variables were divided into two subsets: those that had to be determined before the random uncertainties are disclosed and those (recourse variables) that could be determined

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after the uncertainties were disclosed. Multistage stochastic programming with recourse (MSP) was developed as an extension of dynamic stochastic optimization approaches (Birge, 1985; Pereira and Pinto, 1991; Ruszczynski, 1993; Dupačová et al., 2000; Watkins et al., 2000; Kouwenberg, 2001; Ahmed et al., 2003; Li et al., 2006, 2008). MSP can reflect the dynamic variations of system conditions, particularly for large-scale problems with sequential structures. However, MSP requires probabilistic specifications for uncertain parameters while, in many practical problems, the quality of information that can be obtained is mostly not satisfactory enough to be presented as probabilities (Li et al., 2006). In fact, even if the probability distributions are available, it can be difficult to reflect many random parameters in the MSP model. Moreover, few of the previous studies focused on using MSP methods for addressing uncertainties and dynamics in waste management systems.

Therefore, as an extension to the existing MSP approaches, an inexact fuzzy-stochastic constraint-softened programming method will be developed to address the above deficiencies. The developed method will be able to deal with uncertainties presented in terms of fuzzy sets, interval values, and random variables. Moreover, a number of violation levels for the constraints are allowed, such that the model's decision space can be expanded. This will help generate a range of decision alternatives under various conditions, allowing in-depth analyses of tradeoffs among economic objective, satisfaction degree, and constraint-violation risk. Then, the developed method will be applied to the planning of MSW management in the City of Regina, Canada. It can facilitate dynamic analysis for decisions of waste flow allocation and capacity expansion planning within a multistage context under multiple uncertainties.

2. Methodology

Firstly, consider an interval parameter fuzzy linear programming (IFLP) problem (Huang et al., 1993):

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

$$\text{subject to} \quad A^{\pm}X^{\pm} \,\widetilde{\leq}\, B^{\pm} \tag{1b}$$

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

where $A^{\pm} \in \{R^{\pm}\}^{m\times n}$, $B^{\pm} \in \{R^{\pm}\}^{m\times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1\times n}$, $X^{\pm} \in \{R^{\pm}\}^{n\times 1}$, $\{R^{\pm}\}$ denote a set of interval numbers, and m and n are real numbers ($m \geqslant 1$ and $n \geqslant 1$; $X^{\pm}$ represents a set of decision variables; the '−' and '+' superscripts represent the lower and upper bounds of parameters/variables, respectively; and symbols $\widetilde{=}$ and $\widetilde{\leq}$ represent fuzzy equality and inequality. In fact, a decision in a fuzzy environment can be defined as the intersection of membership functions corresponding to fuzzy objective and constraints (Huang et al., 1995; Chang et al., 1997). Given a fuzzy goal (G) and a fuzzy constraint (E) in a space of decision alternatives ($X^{\pm}$), a fuzzy decision set (D) can then be formed in the intersection of G and E. In a symbolic form, we have $D = G \cap E$, and correspondingly:

$$\mu_D = \text{Min}\{\mu_G, \mu_E\} \tag{2}$$

where μ_D, μ_G and μ_E denote membership functions of fuzzy decision D, fuzzy goal G, and fuzzy constraint E, respectively (Zimmermann, 1985). Let $\mu_{E_i}(X^{\pm})$ be membership functions of constraints E_i (i = 1, 2, ..., m), and $\mu_{G_j}(X^{\pm})$ be those of goals G_j (j = 1, 2, ..., n). A decision can then be defined by the following membership function (Huang et al., 2001):

$$\mu_D(X^{\pm}) = \mu_{E_i}(X^{\pm}) * \mu_{G_j}(X^{\pm}) \tag{3a}$$

$$\mu_D(X^{\pm}) = \text{Min}\{\mu_i(X^{\pm}) | i = 1, 2, \ldots, m+1\} \tag{3b}$$

where "∗" denotes an appropriate and possibly context-dependent "aggregator"; $\mu_i(X^{\pm})$ can be interpreted as the degree to which $X^{\pm}$ satisfies fuzzy inequality in the objective and constraints. A desired decision is thus the one with the highest $\mu_D(X^{\pm})$ value:

$$\text{Max}\mu_D(X^{\pm}) = \text{Max Min}[\mu_i(X^{\pm})], \quad X^{\pm} \geqslant 0 \tag{4}$$

where $\mu_i(X^{\pm})$ should be zero if the objective and constraints are violated, and 1 if they are totally satisfied. Consequently, the IFIP problem can be converted into an ordinary linear programming model by introducing a new variable of $\lambda = \mu_D(X^{\pm})$, which corresponds to the membership function of the fuzzy decision (Zimmermann, 1985; Chang et al., 1997; Huang et al., 2001). Specifically, the flexibility in the constraints and fuzziness in the objective (which are represented by fuzzy sets and denoted as "fuzzy constraints" and "fuzzy goal", respectively) can be expressed as membership grades (λ) corresponding to the degrees of overall satisfaction for the constraints and objective. Thus, model (1) can be converted into:

$$\text{Max} \quad \lambda^{\pm} \tag{5a}$$

$$\text{subject to} \quad C^{\pm}X^{\pm} \leqslant f^{+} - \lambda^{\pm}(f^{+} - f^{-}) \tag{5b}$$

$$A^{\pm}X^{\pm} \leqslant B^{+} - \lambda^{\pm}(B^{+} - B^{-}) \tag{5c}$$

$$X^{\pm} \geqslant 0 \tag{5d}$$

$$0 \leqslant \lambda^{\pm} \leqslant 1 \tag{5e}$$

where f^{-} and f^{+} are the lower and upper bounds of the objective's aspiration level, respectively; $\lambda^{\pm}$ is the control variable corresponding to the degree (membership grade) of satisfaction for the fuzzy decision. An interactive algorithm is developed to solve the above problem through analyzing the detailed interrelationships between the parameters and the variables and between the objective function and the constraints (Huang et al., 1995).

The IFLP can directly handle uncertainties presented as interval numbers and/or fuzzy sets. However, it has difficulties in tackling uncertainties expressed as random variables in a non-fuzzy decision space and in providing a linkage between the pre-regulated policies and the associated implications. In many real-world problems, uncertainties may be expressed as random variables, and the related study systems are of dynamic feature. Thus the relevant decisions must be made at each time stage under varying probability levels. Such a problem can be formulated as a scenario-based multistage stochastic programming (MSP) model with recourse as follows:

$$\text{Min} \quad f = \sum_{t=1}^{T} C_t X_t + \sum_{t=1}^{T} \sum_{k=1}^{K_t} p_{tk} D_{tk} Y_{tk} \tag{6a}$$

$$\text{subject to} \quad A_{rt}X_t \leqslant B_{rt}, \quad r = 1, 2, \ldots, m_1; \quad t = 1, 2, \ldots, T \tag{6b}$$

$$A_{it}X_t + A'_{itk}Y_{tk} \leqslant w_{itk}, \quad i = 1, 2, \ldots, m_2; \quad t = 1, 2, \ldots, T; \quad k = 1, 2, \ldots, K_t \tag{6c}$$

$$x_{jt} \geqslant 0, \quad x_{jt} \in X_t, \quad j = 1, 2, \ldots, n_1; \quad t = 1, 2, \ldots, T \tag{6d}$$

$$y_{jtk} \geqslant 0, \quad y_{jtk} \in Y_{tk}, \quad j = 1, 2, \ldots, n_2; \quad t = 1, 2, \ldots, T; \quad k = 1, 2, \ldots, K_t \tag{6e}$$

where p_{tk} is the probability of occurrence for scenario k in period t, with $p_{tk} \leqslant 0$ and $\sum_{k=1}^{K_t} p_{tk} = 1$; and K_t is the number of scenarios in period t, with the total number of scenarios being $K = \sum_{t=1}^{T} K_t$. In model (6), the decision variables are divided into two subsets: the first-stage decision variables (x_{jt}) that must be determined before the random variables are disclosed, and recourse variables (y_{jtk}) that can be determined after the random variables are disclosed. Obviously, model (6) can address uncertainties in the right-hand sides of the constraints to be presented as random variables. Therefore, one potential approach that can deal with multiple uncertainties presented in terms of fuzzy sets, interval values, and random variables is to couple MSP and IFLP into a general framework; this leads to an interval-fuzzy multistage linear programming (IFMP) model as follows:

$$\text{Max} \quad \lambda^{\pm} \tag{7a}$$

$$\text{subject to} \quad \sum_{t=1}^{T} C_t^{\pm} X_t^{\pm} + \sum_{t=1}^{T} \sum_{k=1}^{K_t} p_{tk} D_{tk}^{\pm} Y_{tk}^{\pm} \leqslant f^{+} - \lambda^{\pm}(f^{+} - f^{-}) \tag{7b}$$

$$A_{rt}^{\pm} X_t^{\pm} \leqslant B_{rt}^{+} - \lambda^{\pm}(B_{rt}^{+} - B_{rt}^{-}), \quad r = 1, 2, \ldots, m_1; \quad t = 1, 2, \ldots, T \tag{7c}$$

$$A_{it}^{\pm} X_t^{\pm} + (A'_{itk})^{\pm} Y_{tk}^{\pm} \leqslant w_{itk}^{+} - \lambda^{\pm} \Delta w_{itk}^{\pm}, \quad i = 1, 2, \ldots, m_2; \quad t = 1, 2, \ldots T; \quad k = 1, 2, \ldots, K_t \tag{7d}$$

$$x_{jt}^{\pm} \geqslant 0, \quad x_{jt}^{\pm} \in X_t^{\pm}, \quad j = 1, 2, \ldots, n_1; \quad t = 1, 2, \ldots, T \tag{7e}$$

$$y_{jtk}^{\pm} \geqslant 0, \quad y_{jtk}^{\pm} \in Y_{tk}^{\pm}, \quad j = 1, 2, \ldots, n_2; \quad t = 1, 2, \ldots, T; \quad k = 1, 2, \ldots, K_t \tag{7f}$$

$$0 \leqslant \lambda^{\pm} \leqslant 1 \tag{7g}$$

In model (7), a $\lambda^{\pm}$ level close to 1 would correspond to a high possibility of satisfying the constraints/objective under advantageous conditions; conversely, a $\lambda^{\pm}$ value near 0 would be related to a solution that has a low possibility of satisfying the constraints/objective under demanding conditions. Model (7) can then be solved through a two-step method. The submodel for λ^{+} corresponding to f^{-} can be formulated in the first step when the system objective is to be minimized; the other submodel for λ^{-} can then be formulated based on the solution of the first submodel. However, the second submodel may often become infeasible due to its strict constraints under demanding conditions; moreover, the decision makers may desire more tradeoff information between system satisfaction degree and constraint-violation risk under uncertainty. One potential alternative for dealing with such issues is to reconfigure the model's decision space through introduction of a number of violation variables (i.e., establishing tolerable levels for the constraints under demanding conditions) into the second submodel (for λ^{-}) to soften its constraints. This leads to a constraint-softened IFMP model. The detailed solution method for the IFMP and the modeling formulation of the constraint-softened IFMP are presented in Appendix 1 to this paper.

3. Case study

The developed method will be applied to the long-term planning of municipal solid waste management in the City of Regina, Canada. Consistent with many communities in western Canada; the city relies mostly on a sanitary landfill for disposing of its MSW. Approximately 70,000 tonnes per year of MSW generated from the residential sector are buried at the landfill. Besides, the city is operating recycling and composting (backyard) programs to encourage residents to reduce the amounts of waste that ends up at the landfill. However, the amount of residential waste diverted from landfill is relatively low (i.e., approximately 12% of the total waste generated by households). In 2000, the Canadian Council of the Ministers of Environment (CCME) adopted a policy guidance for MSW diversion and recycling. Therefore, establishment of regulated waste diversion targets and relevant regulations is currently a growing trend (but not mandatory). Typically, such regulations focus on mandating recovery of specific materials (e.g., dry recyclables and yard wastes), and supporting decisions of appropriate collection systems (e.g., depot, curbside or deposit). To realize the CCME's diversion goal, the city is making efforts to develop an integrated solid waste management (ISWM) strategy for its waste collection, minimization, diversion and disposal. Therefore, this study will focus on increasing waste diversion rate and thus reducing waste flows to the landfill with a minimized system cost.

The study time horizon is 15 years, consisting of three, 5-year periods. Table 1 presents the waste-generation rates and the associated probabilities of occurrence in the planning periods. Many impact factors and their interactions such as population growth rate, economic development, people living habit, and waste management policy could lead to uncertain waste-generation rate (e.g., results of waste characterization study for the city indicate that the residential sector generates waste at a rate of 1.00–1.17 kg/cap/day; the city's population growth rate is in the range of 0.5–0.7% per year). Consequently, in this study, the waste-generation rates are presented in interval-random variables and varied in different periods. There are four levels of waste-generation in period 1 (i.e., low, low-medium, medium and high), and three levels of waste-generation in periods 2 and 3 (i.e., low, medium and high). Since the waste-generation amounts are uncertain, a projected waste flow level is pre-regulated based on the city's waste management policy. If this level is not exceeded, it will result in a regular (normal) cost to the system. However, if it is exceeded, the surplus waste flow will be disposed of at a premium, resulting in an excess cost (penalty) to the system (i.e., excess flow = generated waste – assigned quota). Tables 2 and 3 provide collection and transportation costs for pre-regulated and excess waste flows from the city to the three facilities, operating costs of the three facilities, penalties for surplus flows, and revenues from the composting and recycling facilities. Costs for waste collection and transportation

Table 2
Costs and revenues for pre-regulated waste flows.

	Planning period		
	$t = 1$	$t = 2$	$t = 3$
Operation costs of waste management facilities (CAN\$/t)			
Landfill	[9, 17]	[6.9, 13.02]	[5.83, 11.02]
Composting facility	[21, 26]	[16.09, 19.92]	[13.61, 16.85]
Recycling facility	[61.0, 67.8]	[46.74, 51.95]	[39.54, 43.95]
Collection and transportation costs (CAN\$/t)			
to Landfill	[32, 37]	[24.52, 28.35]	[20.74, 23.98]
to Composting facility	[68.0, 78.2]	[52.09, 59.90]	[44.06, 50.67]
to Recycling facility	[93.0, 108.5]	[71.24, 83.11]	[60.26, 70.31]
Revenues from waste management facilities (CAN\$/t)			
Composting facility	[5.0, 10.0]	[3.83, 7.66]	[3.24, 6.48]
Recycling facility	[45.0, 55.0]	[34.48, 42.14]	[29.17, 35.65]
Residue transportation costs (CAN\$/t)			
Composting facility	[1.68, 2.1]	[1.287, 1.609]	[1.089, 1.36]
Recycling facility	[1.47, 1.68]	[1.126, 1.287]	[0.953, 1.089]

Table 1
Waste-generation rates and the associated probabilities.

Level of waste-generation	$t = 1$		$t = 2$		$t = 3$	
	Probability	Waste flow (t/wk)	Probability	Waste flow (t/wk)	Probability	Waste flow (t/wk)
Low (L)	0.125	[1373, 1433]	0.193	[1418, 1510]	0.185	[1465, 1555]
Low-medium (Lm)	0.280	[1434, 1494]	–	–	–	–
Medium (M)	0.404	[1495, 1577]	0.575	[1511, 1605]	0.605	[1556, 1648]
High (H)	0.191	[1578, 1648]	0.232	[1606, 1702]	0.210	[1649, 1759]

are estimated based on the existing conditions in the collection areas: the average container size, collection frequency, collection mode (automatic and manual), and collection time (per load). The penalty costs for excess waste flows are expressed in terms of raised collection, transportation, and operation costs, significantly higher than the regular ones.

Table 4 shows the relevant waste diversion goals, as well as the minimum and maximum pre-regulated waste flows (to the three facilities). As required by the authorities, 50% diversion of residential waste landfilled would be achievable within the planning horizon. From a long-term planning point of view, waste-generation rates in the city will keep increasing due to the population increase and economic development. The waste management facilities will face problems of insufficiency in their capacities to meet the city's overall waste-disposal demand and waste diversion requirement in the future (e.g., the city plans to develop a centralized composting facility to reduce waste flows to the landfill). Table 5 presents the discounted fixed and variable costs for capacity expansion/development of the three facilities. These cost and revenue data are expressed in present values.

Complexities exist in such a study system, including the collection techniques to be used, the service levels to be offered, and the facilities to be adopted; many related processes and/or factors are complex with multi-period, multi-layer and multi-uncertainty features. Information for many components in waste management systems is not known with certainty. The study problem can thus be formulated as an interval multistage stochastic integer programming (IMSIP) model. In IMSIP, integer programming technique will be used for planning capacity expansion/development of waste management facilities, and fixed-charge cost functions will be employed for reflecting the economies of scale in the expansion/development cost. Thus, we have:

Objective function:

$$
\begin{aligned}
\text{Min}\quad f^{\pm} = {} & \sum_{t=1}^{T} L_t T_{1t}(TR_{1t}^{\pm} + OP_{1t}^{\pm}) \\
& + \sum_{i=2}^{3}\sum_{t=1}^{T} L_t T_{it}[TR_{it}^{\pm} + OP_{it}^{\pm} + FE_i^{\pm}(FT_{it}^{\pm} + OP_{1t}^{\pm}) - RE_{it}^{\pm}] \\
& + \sum_{t=1}^{T}\sum_{k=1}^{K_t} L_t p_{tk} M_{1tk}^{\pm}(DR_{1t}^{\pm} + DP_{1t}^{\pm}) \\
& + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t} L_t p_{tk} M_{itk}^{\pm}[DR_{it}^{\pm} + DP_{it}^{\pm} \\
& + FE_i^{\pm}(DT_{it}^{\pm} + DP_{1t}^{\pm}) - RM_{it}^{\pm}] \\
& + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}(FLC_{1t}^{\pm} Y_{1tk}^{\pm} + VLC_{1t}^{\pm} X_{1tk}^{\pm}) \\
& + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}(FTC_{it}^{\pm} Y_{itk}^{\pm} + VTC_{it}^{\pm} X_{itk}^{\pm})
\end{aligned} \tag{8a}
$$

Constraints:

$$
\sum_{t=1}^{t'} L_t\left[(T_{1t} + M_{1tk}^{\pm}) + \sum_{i=2}^{3} FE_i^{\pm}(T_{it} + M_{itk}^{\pm})\right] \leqslant LC^{\pm} + \sum_{t=1}^{t'} X_{1tk}^{\pm}, \quad t' = 1,2,\ldots,T; \quad k = 1,2,\ldots,K_t \tag{8b}
$$

$$
T_{it} + M_{itk}^{\pm} \leqslant TC_i^{\pm} + \sum_{t=1}^{t'} X_{itk}^{\pm}, \quad t' = 1,2,\ldots,T; \quad i = 2,3; \quad k = 1,2,\ldots,K_t \tag{8c}
$$

$$
\sum_{i=1}^{3}(T_{it} + M_{itk}^{\pm}) = WG_{tk}^{\pm}, \quad \forall t; \quad k = 1,2,\ldots,K_t \tag{8d}
$$

$$
T_{1t} + M_{1tk}^{\pm} \leqslant DG_{1t}^{\pm} WG_{tk}^{\pm}, \quad \forall t; \quad k = 1,2,\ldots,K_t \tag{8e}
$$

$$
T_{it\,\min} \leqslant T_{it} \leqslant T_{it\,\max}, \quad \forall i,t \tag{8f}
$$

$$
0 \leqslant M_{itk}^{\pm} \leqslant T_{it}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{8g}
$$

$$
Y_{itk}^{\pm}\begin{cases} = 1, & \text{if capacity expansion is undertaken} \\ = 0, & \text{if otherwise} \end{cases}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{8h}
$$

$$
0 \leqslant X_{itk}^{\pm} \leqslant N_{itk} Y_{itk}^{\pm}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{8i}
$$

$$
\sum_{t=1}^{t'} Y_{1tk}^{\pm} \leqslant 1, \quad t' = 1,2,\ldots,T; \quad k = 1,2,\ldots,K_t \tag{8j}
$$

The detailed nomenclatures for the variables and parameters are provided in Appendix 2. The objective is to minimize the system cost with desired plans for facility expansion/development and waste flow allocation over the entire planning horizon, which covers (i) expense for handling pre-regulated and probabilistic excess

Table 3
Costs and revenues for excess waste flows.

	Planning period		
	t = 1	t = 2	t = 3
Operation costs of waste management facilities (CAN$/t)			
Landfill	[18, 34]	[13.79, 26.05]	[11.67, 22.04]
Composting facility	[34, 42]	[26.05, 32.18]	[22.04, 27.23]
Recycling facility	[104.0, 115.3]	[79.69, 88.34]	[67.41, 74.74]
Collection and transportation costs (CAN$/t)			
to Landfill	[48.0, 55.5]	[36.77, 42.52]	[31.11, 35.98]
to Composting facility	[102.5, 118.0]	[78.52, 90.39]	[66.42, 76.46]
to Recycling facility	[141.0, 162.5]	[108.01, 124.48]	[91.37, 105.3]
Revenues from waste management facilities (CAN$/t)			
Composting facility	[5.0, 10.0]	[3.83, 7.66]	[3.24, 6.48]
Recycling facility	[45.0, 55.0]	[34.48, 42.14]	[29.17, 35.65]
Residue transportation costs (CAN$/t)			
Composting facility	[2.52, 3.15]	[1.93, 2.41]	[1.63, 2.04]
Recycling facility	[2.21, 2.52]	[1.69, 1.93]	[1.43, 1.63]

Table 4
Pre-regulated waste flow levels and diversion rates.

	Planning period		
	t = 1	t = 2	t = 3
Waste diversion rate			
to Landfill (%)	75	63	50
Minimum pre-regulated waste flow (t/wk)			
to Landfill	700	600	500
to Composting facility	100	250	300
to Recycling facility	200	300	350
Maximum pre-regulated waste flow (t/wk)			
to Landfill	950	850	750
to Composting facility	200	300	400
to Recycling facility	300	400	450

Table 5
Costs for capacity expansion of waste management facilities.

	Planning period		
	t = 1	t = 2	t = 3
Cost for landfill expansion			
Fixed cost (CAN$$10^6$)	[4.04, 4.85]	[3.66, 4.39]	[3.09, 3.72]
Variable cost (CAN$/t)	[2.47, 3.20]	[2.24, 2.90]	[1.89, 2.45]
Cost for composting facility development/expansion			
Fixed cost (CAN$$10^6$)	[2.10, 2.52]	[1.90, 2.28]	[1.61, 1.93]
Variable cost (CAN$/t)	[2.00, 2.58]	[1.81, 2.33]	[1.53, 1.98]
Cost for recycling facility expansion			
Fixed cost (CAN$$10^6$)	[2.78, 30.8]	[2.52, 2.79]	[2.13, 2.36]
Variable cost (CAN$/t)	[6.35, 7.69]	[5.75, 6.96]	[4.86, 5.89]

flows, (ii) revenue from composting and recycling facilities, and (iii) probabilistic expansion/development cost for the three facilities. The constraints define the interrelationships among the decision variables and the waste-generation/management conditions. Among them, constraints (8b) and (8c) denote that the total waste flows to the landfill, composting and recycling facilities must not exceed their existing and expanded capacities; constraint (8d) denotes that, under each scenario, the waste flows handled by the waste management facilities should equal the total waste-generation amount, and this is based on an assumption that there would no mass loss in transportation processes; constraint (8e) denotes that the waste flows disposed of by the landfill should meet the waste diversion goal as pre-regulated by the city's authority; constraint (8f) regulates that each pre-regulated waste flow must between the minimum and maximum pre-regulated levels; constraint (8g) denotes that the excess waste flow to each facility should not exceed the pre-regulated flow level; constraint (8h) defines whether a facility expansion action needs to be undertaken in period t under scenario k; constraint (8i) identifies the amount developed and/or expanded for waste management facilities; and constraint (8j) denotes that the landfill can only be expanded once within the entire planning horizon.

Obviously, the IMSIP model can deal with uncertainties expressed as probability distributions and interval values, and can reflect dynamics in terms of decisions for waste flow allocation and facility capacity expansion, through transactions at discrete points of a complete scenario set over a multistage context. Moreover, it can reflect the effects of economies of scale in expansion costs through introduction of the fixed-charge cost functions. However, the main limitation of the IMSIP model remains in its over-simplification of fuzzy membership information into intervals, resulting in the deficiency of more in-depth analyses for system cost and satisfaction degree.

Therefore, to reflect uncertainties under fuzzy goal and constraints, based on the formulation provided in model (7), the above problem can be reformulated as an interval-fuzzy multistage stochastic integer linear programming (IFMIP) model as follows:

$$\text{Max} \quad \lambda^{\pm} \tag{9a}$$

$$\begin{aligned}\text{subject to} \quad & \sum_{t=1}^{T} L_t T_{1t}(TR_{1t}^{\pm} + OP_{1t}^{\pm}) + \sum_{i=2}^{3}\sum_{t=1}^{T} L_t T_{it}[TR_{it}^{\pm} + OP_{it}^{\pm} \\ & + FE_i^{\pm}(FT_{it}^{\pm} + OP_{1t}^{\pm}) - RE_{it}^{\pm}] \\ & + \sum_{t=1}^{T}\sum_{k=1}^{K_t} L_t p_{tk} M_{1tk}^{\pm}(DR_{1t}^{\pm} + DP_{1t}^{\pm}) \\ & + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t} L_t p_{tk} M_{itk}^{\pm}[DR_{it}^{\pm} + DP_{it}^{\pm} \\ & + FE_i^{\pm}(DT_{it}^{\pm} + DP_{1t}^{\pm}) - RM_{it}^{\pm}] \\ & + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}(FLC_{1t}^{\pm} Y_{1tk}^{\pm} + VLC_{1t}^{\pm} X_{1tk}^{\pm}) \\ & + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}(FTC_{it}^{\pm} Y_{itk}^{\pm} + VTC_{it}^{\pm} X_{itk}^{\pm}) \\ & \leqslant f_{1\text{opt}}^{+} - \lambda^{\pm}\left(f_{1\text{opt}}^{+} - f_{1\text{opt}}^{-}\right)\end{aligned} \tag{9b}$$

$$\begin{aligned}& \sum\nolimits_{t=1}^{t'} L_t\left[(T_{1t}^{\pm} + M_{1tk}^{\pm}) + \sum_{i=2}^{3} FE_i^{\pm}(T_{it}^{\pm} + M_{itk}^{\pm})\right] \\ & \leqslant LC^{+} - \lambda^{\pm}(LC^{+} - LC^{-}) + \sum_{t=1}^{t'} X_{1tk}^{\pm}, \\ & \quad t' = 1, 2, \ldots, T; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{9c}$$

$$\begin{aligned}& T_{it}^{\pm} + M_{itk}^{\pm} \leqslant TC_i^{+} - \lambda^{\pm}(TC_i^{+} - TC_i^{-}) + \sum_{t=1}^{t'} X_{itk}^{\pm} \\ & \quad t' = 1, 2, \ldots, T; \quad i = 2, 3; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{9d}$$

$$\begin{aligned}& \sum_{i=1}^{3}(T_{it}^{\pm} + M_{itk}^{\pm}) = WG_{tk}^{+} - \lambda^{\pm}(WG_{tk}^{+} - WG_{tk}^{-}), \\ & \quad \forall t; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{9e}$$

$$\begin{aligned}& T_{1t}^{\pm} + M_{1tk}^{\pm} \leqslant DG_{1t}[WG_{tk}^{+} - \lambda^{\pm}(WG_{tk}^{+} - WG_{tk}^{-})], \\ & \quad \forall t; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{9f}$$

$$0 \leqslant \lambda^{\pm} \leqslant 1 \tag{9g}$$

$$0 \leqslant M_{itk}^{\pm} \leqslant T_{it}, \quad \forall i, t; \quad k = 1, 2, \ldots, K_t \tag{9h}$$

The constraints for facility capacity expansion are the same as those in model (8) [i.e., constraints (8h) to (8j)]. The $f_{1\text{opt}}^{-}$ and $f_{1\text{opt}}^{+}$ are the lower and upper bounds of objective function value obtained from model (8). Obviously, IFMIP can deal with multiple uncertainties presented in terms of probability distributions, interval numbers, and fuzzy sets. More importantly, it can produce solutions for not only the decision variables and the objective function but also the satisfaction degree for system objective and constraints under uncertainty. Higher $\lambda^{\pm}$ levels correspond to less strict system constraints, which represent a higher satisfaction degree for the objective/constraints under advantageous conditions; meanwhile, a higher $\lambda^{\pm}$ level is associated with a lower system cost. Conversely, a lower $\lambda^{\pm}$ level (a lower satisfaction degree) corresponds to more strict constraints under demanding conditions, resulting in a higher system cost. Therefore, a number of violation variables (under fuzzy goal and constraints) can be introduced into model (9) for obtaining alternatives under various risk levels of constraint-violation. A constraint-softened IFMIP model can then be formulated as follows:

$$\text{Max} \quad \lambda^{-} \tag{10a}$$

$$\begin{aligned}\text{subject to} \quad & \sum_{t=1}^{T} L_t T_{1t}(TR_{1t}^{+} + OP_{1t}^{+}) + \sum_{i=2}^{3}\sum_{t=1}^{T} L_t T_{it}[TR_{it}^{+} + OP_{it}^{+} \\ & + FE_i^{+}(FT_{it}^{+} + OP_{1t}^{+}) - RE_{it}^{-}] \\ & + \sum_{t=1}^{T}\sum_{k=1}^{K_t} L_t p_{tk} M_{1tk}^{+}(DR_{1t}^{+} + DP_{1t}^{+}) \\ & + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t} L_t p_{tk} M_{itk}^{+}[DR_{it}^{+} + DP_{it}^{+} \\ & + FE_i^{+}(DT_{it}^{+} + DP_{1t}^{+}) - RM_{it}^{-}] \\ & + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}(FLC_{1t}^{+} Y_{1tk}^{+} + VLC_{1t}^{+} X_{1tk}^{+}) \\ & + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}(FTC_{it}^{+} Y_{itk}^{+} + VTC_{it}^{+} X_{itk}^{+}) - V_f \\ & \leqslant f_{1\text{opt}}^{+} - \lambda^{-}\left(f_{1\text{opt}}^{+} - f_{1\text{opt}}^{-}\right)\end{aligned} \tag{10b}$$

$$\begin{aligned}& \sum_{t=1}^{t'} L_t\left[(T_{1t} + M_{1tk}^{+}) + \sum_{i=2}^{3} FE_i^{+}(T_{it} + M_{itk}^{+})\right] \\ & - V_{LC} \leqslant LC^{+} - \lambda^{-}(LC^{+} - LC^{-}) + \sum_{t=1}^{t'} X_{1tk}^{+}, \\ & t' = 1, 2, \ldots, T; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{10c}$$

$$\begin{aligned}& T_{it} + M_{itk}^{+} - V_{TC_i} \leqslant TC_i^{+} - \lambda^{-}(TC_i^{+} - TC_i^{-}) \\ & + \sum_{t=1}^{t'} X_{itk}^{+}, \\ & t' = 1, 2, \ldots, T; \quad i = 2, 3; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{10d}$$

$$\begin{aligned}& \sum_{i=1}^{3}(T_{it} + M_{itk}^{+}) + V_{WG_{tk}} \\ & = WG_{tk}^{+} - \lambda^{-}(WG_{tk}^{+} - WG_{tk}^{-}), \\ & \forall t; \quad k = 1, 2, \ldots, K_t\end{aligned} \tag{10e}$$

$$T_{1t} + M^{+}_{1tk} - V_{DG} \leqslant DG_{1t}\left[WG^{+}_{tk} - \lambda^{-}\left(WG^{+}_{tk} - WG^{-}_{tk}\right)\right],$$
$$\forall t; \quad k = 1,2,\ldots, \quad K_t \tag{10f}$$

$$\frac{2V_f}{(f^{-}_{1\mathrm{opt}} + f^{+}_{1\mathrm{opt}})} + \sum_{t=1}^{T}\sum_{k=1}^{K_t}\frac{2V_{LC}}{(LC^{-} + LC^{+})} + \sum_{i=2}^{3}\sum_{t=1}^{T}\sum_{k=1}^{K_t}\frac{2V_{TCi}}{(TC^{-}_i + TC^{+}_i)} + \sum_{t=1}^{T}\sum_{k=1}^{K_t}\frac{2V_{WG}}{(WG^{-}_{tk} + WG^{+}_{tk})} + \sum_{t=1}^{T}\sum_{k=1}^{K_t}\frac{2V_{DG}}{DG_{1t}(WG^{-}_{tk} + WG^{+}_{tk})} \leqslant TV \tag{10g}$$

$$T_{it\,\min} \leqslant T_{it} \leqslant T_{it\,\max}, \quad \forall i,t \tag{10h}$$

$$Y^{+}_{itk}\begin{cases} = 1, & \text{if capacity expansion is undertaken} \\ = 0, & \text{if otherwise}\end{cases},$$
$$\forall i,t; \quad k = 1,2,\ldots,K_t \tag{10i}$$

$$\sum_{t=1}^{t'} Y^{+}_{1tk} \leqslant 1, \quad t' = 1,2,\ldots,T; \quad k = 1,2,\ldots,K_t \tag{10j}$$

$$X^{+}_{itk} \leqslant N_{itk}Y^{+}_{itk}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{10k}$$

$$0 \leqslant \lambda^{-} \leqslant 1 \tag{10l}$$

$$M^{-}_{itkopt} \leqslant M^{+}_{itk} \leqslant T_{it}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{10m}$$

$$X^{+}_{itk} \geqslant X^{-}_{itkopt}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{10n}$$

$$Y^{+}_{itk} \geqslant Y^{-}_{itkopt}, \quad \forall i,t; \quad k = 1,2,\ldots,K_t \tag{10o}$$

The detailed nomenclatures for the variables and parameters are provided in Appendix 2. For example, WG^{-}_{tk} and WG^{+}_{tk} denote the lower and upper bounds of waste-generation rate ($G^{\pm}_{tk}$) in period t under scenario k (tonne/week), respectively. The M^{-}_{itkopt}, X^{-}_{itkopt} and Y^{-}_{itkopt} are solutions for waste flow allocation and capacity expansion from the submodel [of model (9)] corresponding to λ^{+} . TV denotes the total violation level. When $TV = 0$, the goal and constraints will not be violated. However, when $TV > 0$, the corresponding constraint is allowed to be relaxed, associated with a given risk level of constraint-violation. Thus, the solutions from model (10) can

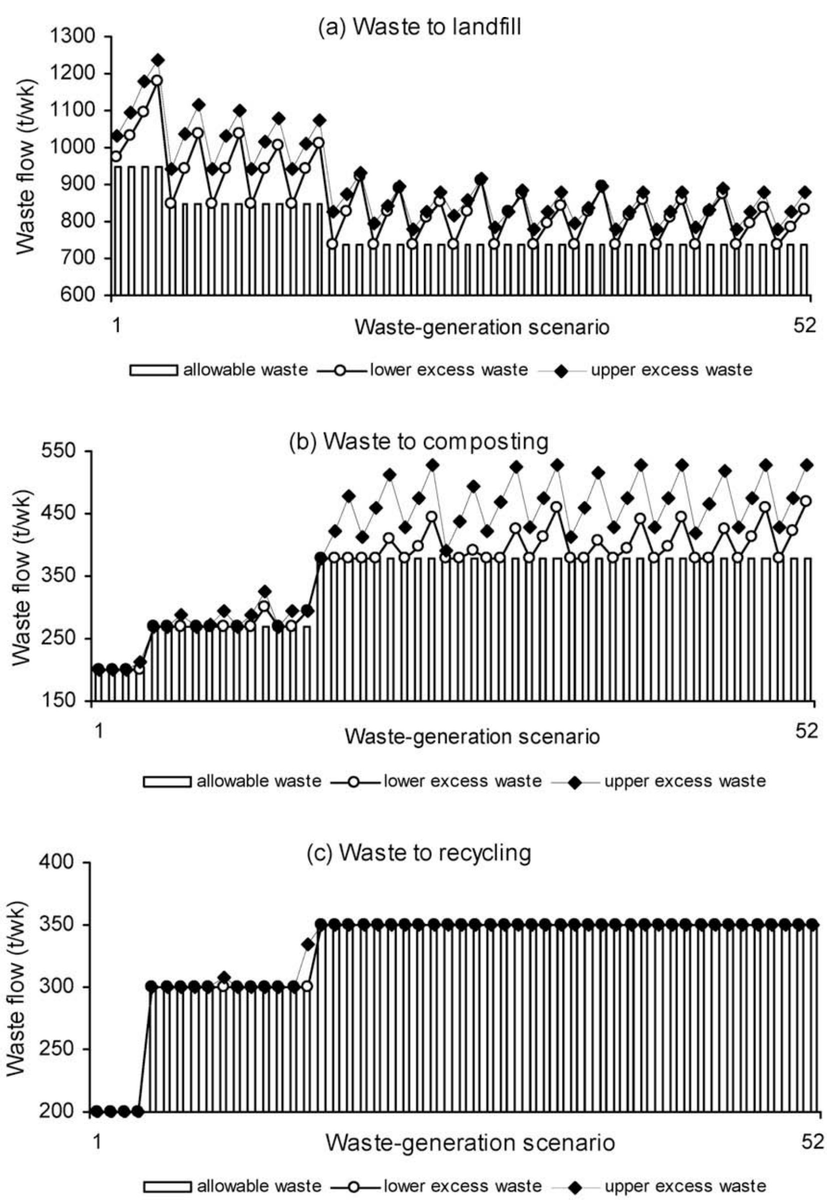

Fig. 1. Solution for waste flow allocation from the IMSIP model.

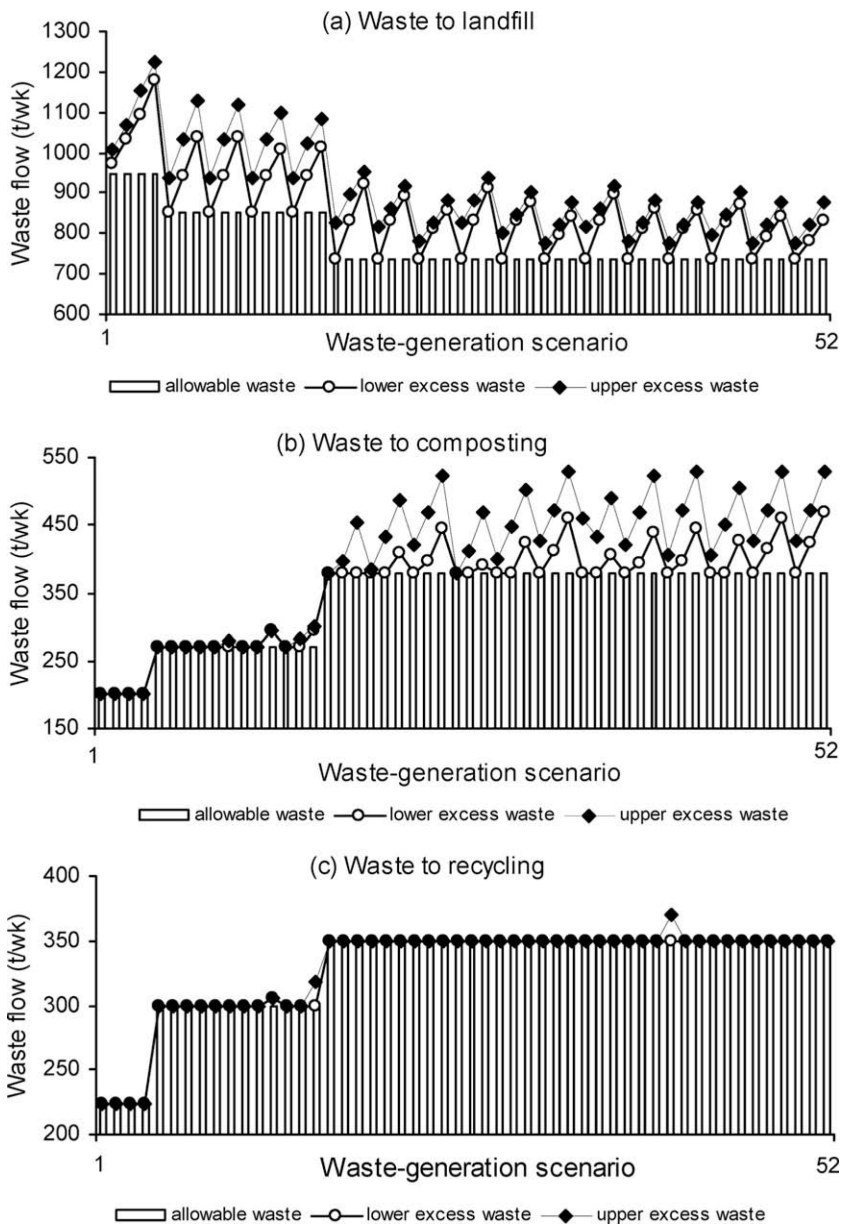

Fig. 2. Waste flow allocation pattern from the IFMIP model.

help quantify relationships among the system cost, satisfaction degree, and constraint-violation risk under various conditions. This is meaningful for supporting further in-depth analyses of tradeoffs between environmental and economic objectives as well as those between system optimality and reliability.

4. Result analysis

Fig. 1 provides the solutions for waste flow allocation patterns obtained from the IMSIP model [i.e., model (8)]; they include pre-regulated and excess flows from the city to the landfilling, composting and recycling facilities over the planning horizon. A multi-layer scenario tree was constructed for reflecting uncertainties, resulting in a total of 52 scenarios. Scenario 1 denotes a low waste-generation rate in period 1 with a probability of 12.5%; scenario 52 corresponds to high waste-generation rates in the three periods with a joint probability of 0.93%. The waste flow-allocation patterns would vary under different scenarios, due to the temporal and spatial variations of waste-generation and management conditions. For example, when waste-generation rates are medium in all of the three periods (with a joint probability of 14.1%), waste flows allocated to the landfill would be [1095, 1177], [943.0, 1016.9] and [813.2, 824.0] t/wk in periods 1, 2 and 3, respectively; waste flows

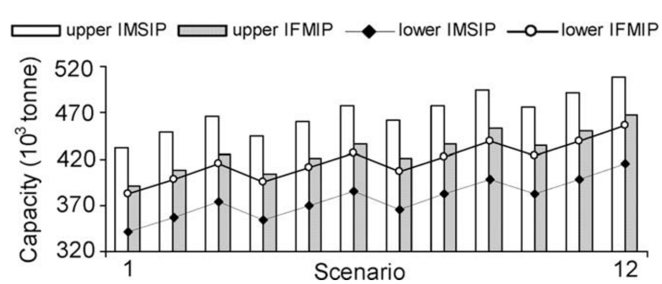

Fig. 3. Expansion schemes for the landfill.

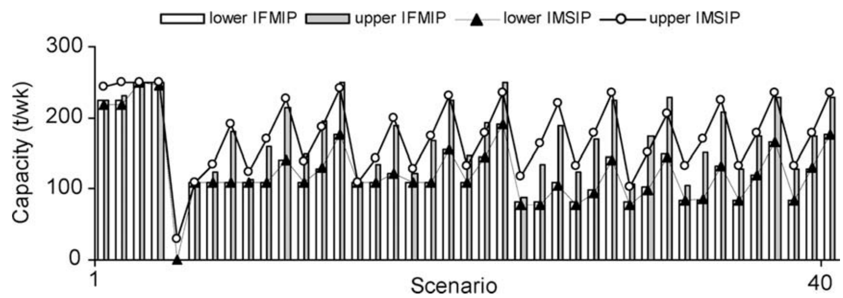

Fig. 4. Expansion schemes for the composting facility.

to the composting facility would be 200 [268.0, 288.1], and [392.8, 474.0] t/wk in periods 1, 2 and 3, respectively; and waste flows to the recycling facility would be 200, 300 and 350 t/wk in periods 1, 2 and 3, respectively. The waste flows to the landfill would be decreasing along with time, while those to the composting and recycling facilities would keep increasing, to satisfy the required diversion goal. Fig. 2 presents the solutions of IFMIP [i.e., model (9)] regarding waste flow allocation; they are different from those obtained from the IMSIP model. For example, when waste-generation rates are medium in all of the three periods, waste flows allocated to the landfill would be [1034.5, 1069.7], [943.0, 1034.2] and [813.9, 827.9] t/wk in periods 1, 2 and 3, respectively.

Fig. 3 shows the solutions for landfill-capacity expansion schemes through IMSIP and IFMIP models. The results (from both IMSIP and IFMIP) indicate that the landfill would be expanded at the start of period 2, and no expansion would be undertaken in periods 1 and 3. However, the expanded capacities (from IMSIP and IFMIP) are different from each other. For example, when waste-generation rates are low over the planning horizon, the expanded capacity would be [340.7, 432.4] $\times 10^3$ tonne (from IMSIP) and [381.7, 391.5] $\times 10^3$ tonne (from IFMIP). Moreover, varying waste-generation rates would lead to different incremental requirements for the landfill expansion. For instance, when waste-generation rates are high in all of the three periods, the expanded capacities would be [414.6, 508.8] $\times 10^3$ tonne (from IMSIP) and [455.6, 467.7] $\times 10^3$ tonne (from IFMIP).

The results of IMSIP and IFMIP regarding the expansion schemes for the composting facility are shown in Fig. 4. The composting facility would be expanded under most of the scenarios over the planning horizon. The expansion plans from IMSIP and IFMIP would also be different from each other. For example, when waste-generation rates are medium in period 1 and high in periods 2 and 3, the results of IMSIP indicate that the composting facility would be developed with a capacity of 250 t/wk in period 1 followed with two expansions of [0, 29.0] t/wk in period 2 and [144.5, 205.5] t/wk in period 3; this facility would thus be developed once and expended twice and the total increment of capacity would be [394.5, 484.5] t/wk. In comparison, the results of IFMIP indicate that, under this waste-generation scenario, the composting facility would be developed once (in period 1) and expanded once (in period 3), and the total increment of capacity would be [398.6, 479.4] t/wk. The results of IMSIP and IFMIP indicate that there would be one expansion option for the recycling facility over the planning horizon; this facility would be expanded at the start of period 1 with increments of [168, 189] t/wk under IMSIP and 188.8 t/wk under IFMIP.

The expected system cost obtained from the IMSIP model would be $f^{\pm}_{\text{opt}}$ = CAN\$[69.96, 96.89] $\times 10^6$; the system cost from IFMIP would be CAN\$[70.20, 96.33] million associated with a satisfaction degree ($\lambda^{\pm}$) of [0.02, 0.99]. In comparison, IFMIP can lead to a narrower interval for system cost than IMSIP. Besides, IFMIP can more effectively specify the variety of uncertainties through provision of additional $\lambda^{\pm}$ information. The $\lambda^{\pm}$ level represents the possibility of satisfying the objective and constraints. It corresponds to the decision makers' preference regarding environmental and economic tradeoffs. In detail, λ^- corresponds to a higher system cost (f^+) under demanding conditions (i.e., with a higher waste-generation rate and a lower facility capacity); λ^+ is related to f^- under advantageous conditions associated with a lower waste-generation rate. Consequently, planning with a higher system cost would guarantee that the waste management requirements and environmental regulations be met. However, the lower bound of $\lambda^{\pm}$ (i.e., λ^- corresponding to f^+) is merely 0.02, indicating a relatively low possibility of satisfying the objective and constraints.

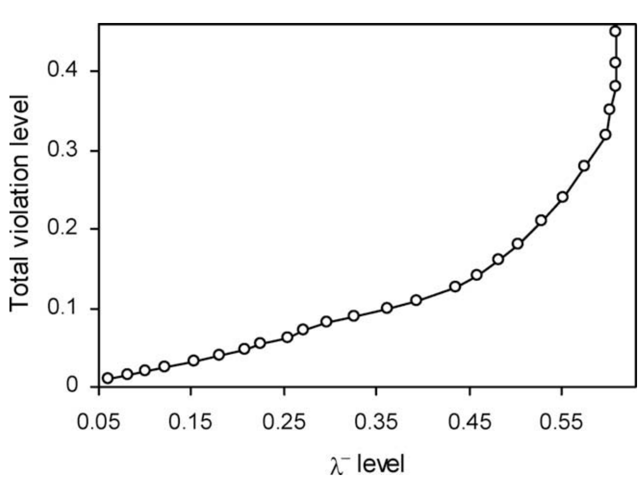

Fig. 5. Relationship between total violation and λ^- levels.

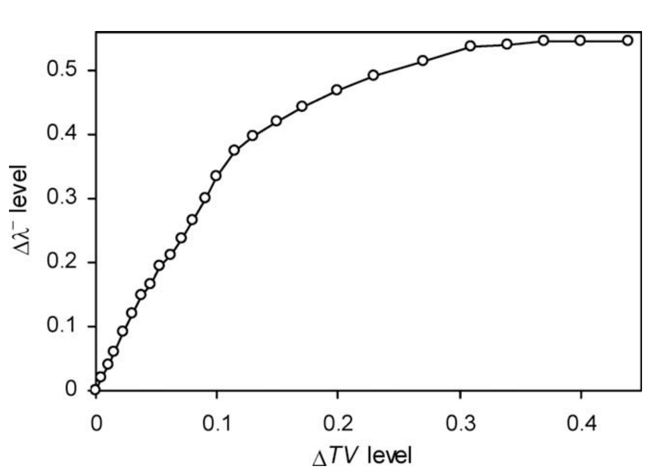

Fig. 6. Relationship between $\Delta\lambda^-$ and ΔTV.

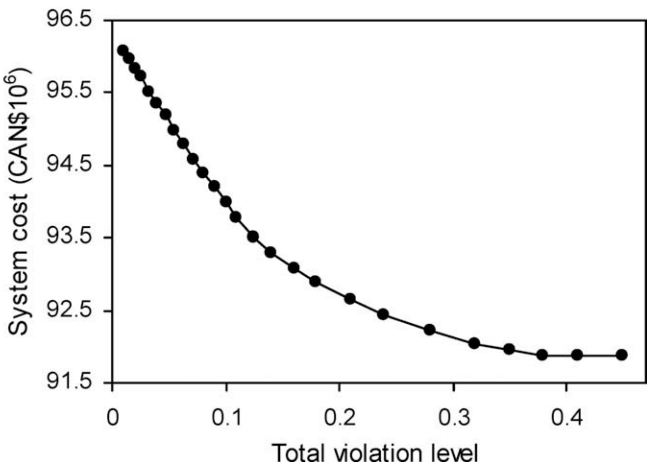

Fig. 7. Relationship between system cost and total violation level.

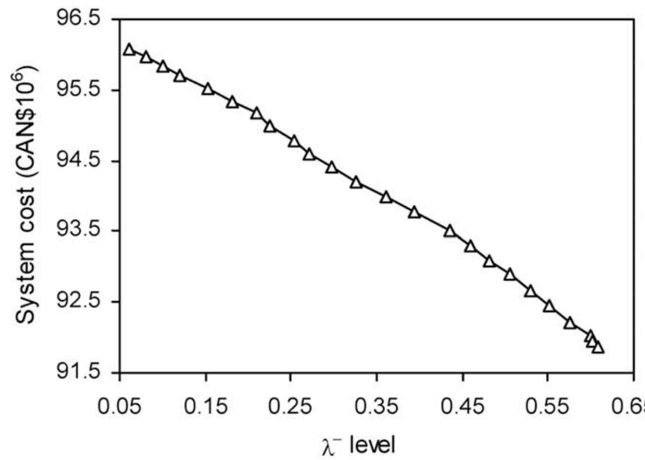

Fig. 9. System costs under different λ^- levels.

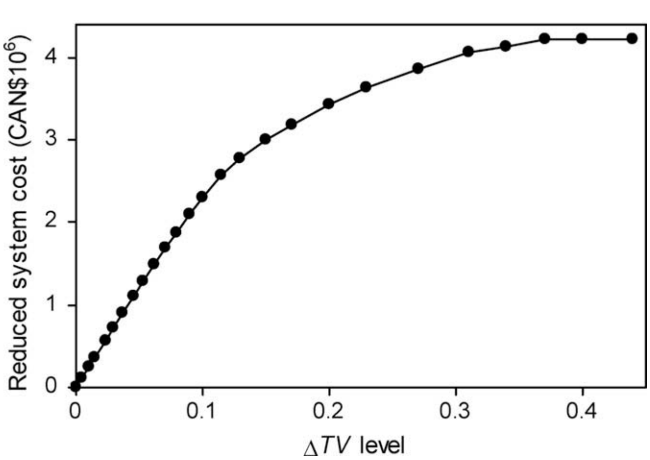

Fig. 8. Relationship between reduced system cost and ΔTV.

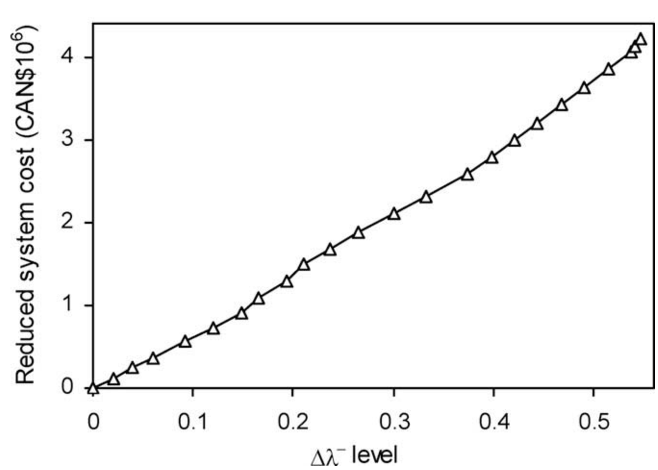

Fig. 10. Reduced system cost under different $\Delta\lambda^-$ levels.

In model (10), a number of violation variables were introduced to soften the system constraints under demanding conditions. A total of 26 conditions corresponding to different violation levels were analyzed to obtain insight into the variations of system cost (f^+) and satisfaction degree (λ^-) under different risk levels of violating constraints. Violation analyses could help investigate the risks of violating the system constraints and generate a range of decision alternatives. Through solving the constraint-softened IFMIP model under various levels of allowable violations for system constraints, relationships between λ^- and constraint-violation levels can be obtained, as shown in Fig. 5. An increased total violation level would lead to a raised λ^- level. When $TV = 0.38$, the λ^- level would increase to 0.61; however, this increase also corresponds to a raised constraint-violation risk. Fig. 6 presents the relationship between the increment of λ^- value ($\Delta\lambda^-$) and variation of total violation level (ΔTV), where condition 1 ($\lambda^- = 0.06$ and $TV = 0.01$) is used as the reference one. The results indicate that, when ΔTV is greater than 0.37, λ^- value would not increase (i.e., $\Delta\lambda^- = 0$). This implies that the system would achieve its highest satisfaction degree ($\lambda^- = 0.61$) when $TV = 0.38$.

Fig. 7 presents the results for system cost under various violation levels. An increased violation level (i.e., softened system constraint) would lead to a decreased system cost. The relationship between the cost reduction and violation-level variation is shown in Fig. 8. The results indicate that, when ΔTV is greater than 0.37, system cost would not decrease (i.e., $\Delta f^- = 0$). Correspondingly, the lowest system cost (CAN$91.87 million) would be achieved when $TV = 0.38$. Therefore, the results indicate that the system would achieve both the highest satisfaction degree and the lowest cost under $TV = 0.38$. Generally, the system cost would decrease and the satisfaction degree would increase as the violation level is raised; however, when the total violation level for the constraints increases to a limit, the system cost would not decrease and the satisfaction degree would also not increase.

A number of violation analyses were conducted to obtain insight into the variations of the cost reduction under different λ^- levels. Fig. 9 presents the relationship between the system cost and λ^- level. The relationship between the reduced cost and $\Delta\lambda^-$ level is also depicted in Fig. 10. Generally, the system cost would decrease as the λ^- level increases; an increased λ^- level means an increased satisfaction degree for the objective and constraints. Therefore, a decision at a lower λ^- level would lead to a lower satisfaction degree, but with a higher system cost; in comparison, decisions at higher λ^- levels would result in lower system costs but, at the same time, higher risk levels of violating the constraints.

Different violation levels correspond to varied λ^- levels. Varied λ^- levels would lead to varying relationships between waste-generation rates and waste-treatment capacities, and thus result in different waste flow allocation patterns. Fig. 11 presents the solutions of waste flows (the sum of pre-regulated and excess flows) to the landfilling and composting facilities under several λ^- levels. For example, when waste-generation rates are high in all of the three

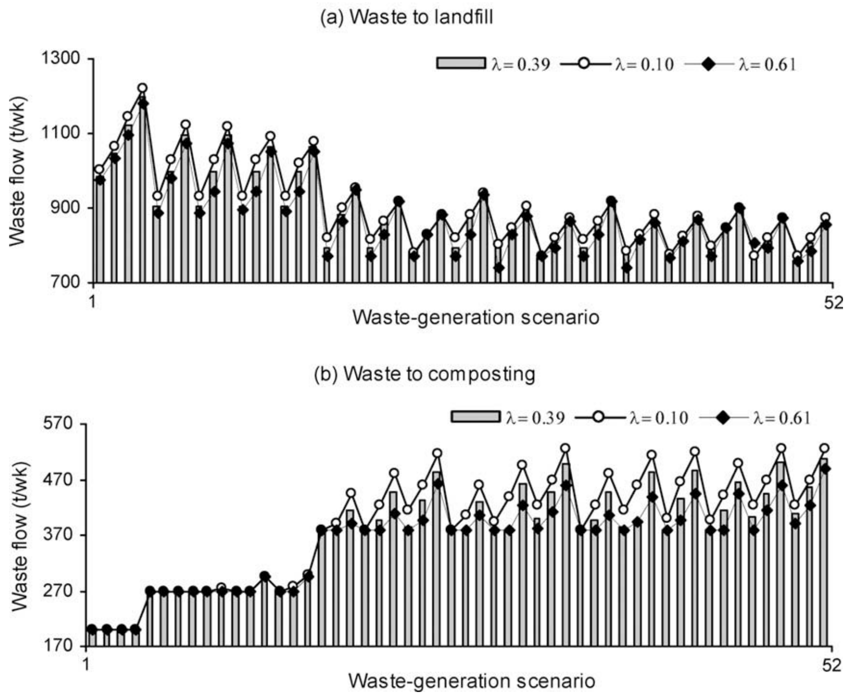

Fig. 11. Waste flows to the landfill and composting facility under different λ^- levels.

periods, the waste flows allocated to the landfilling and composting facilities would be (i) 826.7×10^3 and 266.6×10^3 tonnes when λ^- = 0.10, (ii) 813.8×10^3 and 262.1×10^3 tonnes when λ^- = 0.39, and (iii) 804.5×10^3 and 256.2×10^3 tonnes when λ^- = 0.61, respectively. In comparison, the waste to the recycling facility would have insignificant variation with λ^- level. This is because

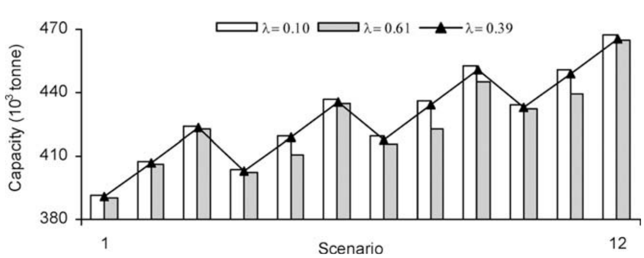

Fig. 12. Expansion schemes for the landfill under different λ^- levels.

the recycling facility has the highest operating cost for waste flows and the highest capital cost for capacity expansion, so that the majority of waste flows would be firstly allocated to the landfill and/or composting facility.

Figs. 12 and 13 present the expansion plans for the landfill and composting facility under different λ^- levels. The results demonstrate that a raised λ^- level would lead to a reduced capacity expansion plan. For example, when waste-generation rates are high over the planning horizon, the expanded capacities for the landfill would be 467.3×10^3 tonne when λ^- = 0.10, 465.7×10^3 tonne when λ^- = 0.39, and 464.6×10^3 tonne when λ^- = 0.61; the total expanded capacities for the composting facility would be 475.3, 460.4 and 441.5 t/wk when λ^- = 0.10, 0.39, and 0.61, respectively. An increased λ^- level corresponds to a reduced waste-disposal amount and a raised waste-treatment capacity; lower waste-disposal amount and higher waste-treatment capacity could both result in a lower capacity expansion plan and a lower capital cost for facility expansion. However, an increased λ^- level is also associated with a raised risk of violating the constraints.

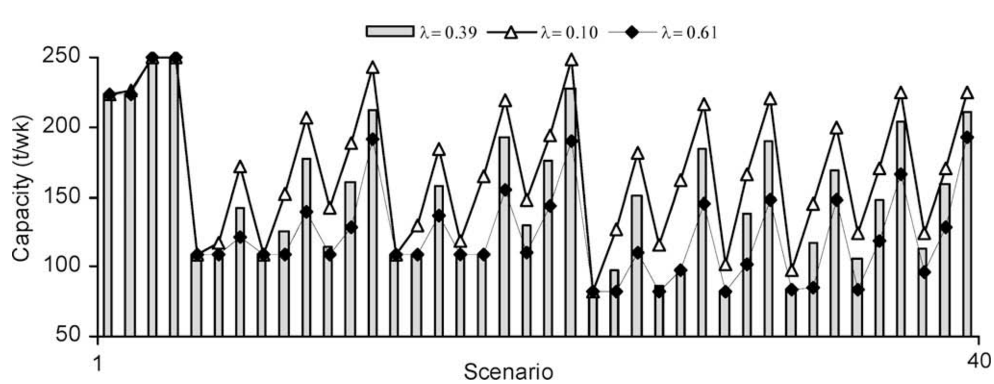

Fig. 13. Expansion schemes for the composting facility under different λ^- levels.

5. Conclusions

In this study, an inexact fuzzy-stochastic constraint-softened programming method has been developed for violation analyses of solid waste management systems under uncertainty. The developed method can handle uncertainties presented in terms of fuzzy sets, random variables, and interval numbers, and can reflect dynamics of the uncertainties and the relevant decisions within a multistage context. Moreover, in the modeling formulation, recourse actions against any infeasibilities arising due to particular realizations of the uncertainties have been taken into account to minimize the economic penalties due to improper policies. Furthermore, a number of violation variables for the constraints have been introduced; this can help generate a range of decision alternatives under various conditions, allowing in-depth analyses of tradeoffs among economic objective, satisfaction degree, and constraint-violation risk.

The developed method has been applied to supporting long-term planning of a municipal solid waste management system. Integer programming technique has been introduced into the modeling formulation to facilitate dynamic analysis for decisions of timing, sizing and siting in planning capacity expansion/development for waste management facilities. The results indicate that potentially useful information has been obtained through the developed method. They can help to identify desired capacity expansion/development and waste flow-allocation plans and to analyze the tradeoffs among the system cost, satisfaction degree, and constraint-violation risk. Generally, a decision at a lower λ^- level would lead to an increased system reliability but with a higher system cost; conversely, decisions at higher λ^- levels would result in lower system costs but higher risks of violating the constraints.

Acknowledgements

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Appendix 1. Solution method

A two-step method is proposed for solving the IFMP model. The submodel for λ^+ corresponding to f^- can be formulated in the first step when the system objective is to be minimized; the other submodel (corresponding to f^+) can then be formulated based on the solution of the first submodel. Thus, the first submodel is formulated (assume that $B^{\pm} > 0$ and $f^{\pm} > 0$) as follows:

$$\text{Max} \quad \lambda^+ \tag{11a}$$

$$\text{subject to} \quad \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c_{jt}^- x_{jt}^- + \sum_{j=j_1+1}^{n_1} c_{jt}^- x_{jt}^+\right) + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}\left(\sum_{j=1}^{j_2} d_{jtk}^- y_{jtk}^- + \sum_{j=j_2+1}^{n_2} d_{jtk}^- y_{jtk}^+\right) \leqslant f^+ - \lambda^+(f^+ - f^-) \tag{11b}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^+ \text{Sign}(a_{rjt}^+) x_{jt}^- + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^- \text{Sign}(a_{rjt}^-) x_{jt}^+ \leqslant b_{rt}^+ - \lambda^+(b_{rt}^+ - b_{rt}^-), \forall r, t \tag{11c}$$

$$\sum_{j=1}^{j_1} |\, a_{ijt}|^+ \text{Sign}(a_{ijt}^+) x_{jt}^- + \sum_{j=j_1+1}^{n_1} |\, a_{ijt}|^- \text{Sign}(a_{ijt}^-) x_{jt}^+ + \sum_{j=1}^{j_2} |\, a_{ijtk}'^+ \,| \text{Sign}(a_{ijtk}'^+) y_{jtk}^- + \sum_{j=j_2+1}^{n_2} |a_{ijtk}'|^- \text{Sign}(a_{ijt}'^-) y_{jtk}^+ \leqslant w_{itk}^+ - \lambda^+(w_{itk}^+ - w_{itk}^-),$$

$$\forall i, t; \quad k = 1, 2, \ldots, K_t \tag{11d}$$

$$x_{jt}^- \geqslant 0, \quad \forall t;\ j = 1, 2, \cdots, j_1 \tag{11e}$$

$$x_{jt}^+ \geqslant 0, \quad \forall t;\ j = j_1 + 1, j_1 + 2, \ldots, n_1 \tag{11f}$$

$$y_{jtk}^- \geqslant 0, \quad \forall t;\ j = 1, 2, \ldots, j_2;\ k = 1, 2, \ldots, K_t \tag{11g}$$

$$y_{jtk}^+ \geqslant 0, \quad \forall t;\ j = j_2 + 1, j_2 + 2, \ldots, n_2;\ k = 1, 2, \ldots, K_t \tag{11h}$$

$$0 \leqslant \lambda^+ \leqslant 1 \tag{11i}$$

where $x_{jt}^{\pm}$ ($j = 1, 2, \ldots, j_1$) are the first-stage decision variables with positive coefficients in the objective function, and $x_{jt}^{\pm}$ ($j = j_1 + 1, j_1 + 2, \ldots, n_1$) with negative coefficients; $y_{jtk}^{\pm}$ ($k = 1, 2, \ldots, K_t$ and $j = 1, 2, \ldots, j_2$) are the second-stage decision variables with positive coefficients in the objective function, and $y_{jtk}^{\pm}$ ($k = 1, 2, \ldots, K_t$ and $j = j_2 + 1, j_2 + 2, \ldots, n_2$) with negative coefficients. Solutions of x_{jtopt}^- ($j = 1, 2, \ldots, j_1$), x_{jtopt}^+ ($j = j_1 + 1, j_1 + 2, \ldots, n_1$), y_{jtkopt}^- ($j = 1, 2, \ldots, j_2$ and $k = 1, 2, \ldots, K_t$), y_{jtkopt}^+ ($j = j_2 + 1, j_2 + 2, \ldots, n_2$ and $k = 1, 2, \ldots, K_t$) and λ_{opt}^+ can be obtained from submodel (11). Based on the above solutions, the second submodel for λ^- (corresponding to f^+) can be formulated as follows:

$$\text{Max} \quad \lambda^- \tag{12a}$$

$$\text{subject to} \quad \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c_{jt}^+ x_{jt}^+ + \sum_{j=j_1+1}^{n_1} c_{jt}^+ x_{jt}^-\right) + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}\left(\sum_{j=1}^{j_2} d_{jtk}^+ y_{jtk}^+ + \sum_{j=j_2+1}^{n_2} d_{jtk}^+ y_{jtk}^-\right) \leqslant f^+ - \lambda^-(f^+ - f^-) \tag{12b}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^- \text{Sign}(a_{rjt}^-) x_{jt}^+ + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^+ \text{Sign}(a_{rjt}^+) x_{jt}^- \leqslant b_{rt}^+ - \lambda^-(b_{rt}^+ - b_{rt}^-), \quad \forall r, t \tag{12c}$$

$$\sum_{j=1}^{j_1} |\, a_{ijt}|^- \text{Sign}(a_{ijt}^-) x_{jt}^+ + \sum_{j=j_1+1}^{n_1} |\, a_{ijt}|^+ \text{Sign}(a_{ijt}^+) x_{jt}^- + \sum_{j=1}^{j_2} |\, a_{ijtk}'|^- \text{Sign}(a_{ijtk}'^-) y_{jtk}^+ + \sum_{j=j_2+1}^{n_2} |\, a_{ijtk}'|^+ \text{Sign}(a_{ijtk}'^+) y_{jtk}^- \leqslant w_{itk}^+ - \lambda^-(w_{itk}^+ - w_{itk}^-),$$

$$\forall i, t;\ k = 1, 2, \ldots, K_t \tag{12d}$$

$$x_{jt}^+ \geqslant x_{jtopt}^-, \quad \forall t;\ j = 1, 2, \ldots, j_1 \tag{12e}$$

$$0 \leqslant x_{jt}^- \leqslant x_{jtopt}^+, \quad \forall t;\ j = j_1 + 1,\ j_1 + 2, \ldots, n_1 \tag{12f}$$

$$y_{jtk}^+ \geqslant y_{jtkopt}^-, \ \forall t;\ j = 1, 2, \ldots, j_2;\ k = 1, 2, \ldots, K_t \tag{12g}$$

$$0 \leqslant y_{jtk}^- \leqslant y_{jtkopt}^+, \quad \forall t;\ j = j_2 + 1, j_2 + 2, \ldots, n_2;\ k = 1, 2, \ldots, K_t \tag{12h}$$

$$0 \leqslant \lambda^- \leqslant 1 \tag{12i}$$

Solutions of x_{jtopt}^+ ($j = 1, 2, \ldots, j_1$), x_{jtopt}^- ($j = j_1 + 1, j_1 + 2, \ldots, n_1$), y_{jtkopt}^+ ($j = 1, 2, \ldots, j_2$ and $k = 1, 2, \ldots, K_t$), y_{jhopt}^- ($j = j_2 + 1, j_2 + 2, \ldots, n_2$ and $k = 1, 2, \ldots, K_t$) and λ_{opt}^- can be obtained through solving submodel (12). Therefore, combining solutions of submodels (11) and (12), we have solution for the IFMP model as follows:

$$x^{\pm}_{jtopt} = \left[x^{-}_{jtopt}, x^{+}_{jtopt}\right], \quad \forall j, t \tag{13a}$$

$$y^{\pm}_{jtkopt} = \left[y^{-}_{jtkopt} y^{+}_{jtkopt}\right], \quad \forall j, t;\ k = 1, 2, \ldots, K_t \tag{13b}$$

$$\lambda^{\pm}_{opt} = \left[\lambda^{-}_{opt}, \lambda^{+}_{opt}\right] \tag{13c}$$

$$f^{\pm}_{opt} = \left[f^{-}_{opt}, f^{+}_{opt}\right] \tag{13d}$$

However, the second submodel may often become infeasible due to its strict constraints under demanding conditions. One potential alternative for dealing with such issues is to reconfigure the model's decision space through introduction of a number of violation variables (i.e., establishing tolerable levels for the constraints under demanding conditions) into the second submodel to soften its constraints. This leads to a constraint-softened IFMP model (for λ^-) as follows:

$$\text{Max} \quad \lambda^- \tag{14a}$$

$$\text{subject to} \quad \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c^{+}_{jt} x^{+}_{jt} + \sum_{j=j_1+1}^{n_1} c^{+}_{jt} x^{-}_{jt}\right) + \sum_{t=1}^{T}\sum_{k=1}^{K_t} p_{tk}\left(\sum_{j=1}^{j_2} d^{+}_{jtk} y^{+}_{jtk} + \sum_{j=j_2+1}^{n_2} d^{+}_{jtk} y^{-}_{jtk}\right) - V_f \leqslant f^+ - \lambda^-(f^+ - f^-) \tag{14b}$$

$$\sum_{j=1}^{j_1} |a_{rjt}|^- \mathrm{Sign}(a^{-}_{rjt}) x^{+}_{jt} + \sum_{j=j_1+1}^{n_1} |a_{rjt}|^+ \mathrm{Sign}(a^{+}_{rjt}) x^{-}_{jt} - V_{rt} \leqslant b^{+}_{rt} - \lambda^-(b^{+}_{rt} - b^{-}_{rt}), \quad \forall r, t \tag{14c}$$

$$\sum_{j=1}^{j_1} |\, a_{ijt}|^- \mathrm{Sign}(a^{-}_{ijt}) x^{+}_{jt} + \sum_{j=j_1+1}^{n_1} |\, a_{ijt}|^+ \mathrm{Sign}(a^{+}_{ijt}) x^{-}_{jt} + \sum_{j=1}^{j_2} |\, a'_{ijtk}|^- \mathrm{Sign}(a'^{-}_{ijtk}) y^{+}_{jtk} + \sum_{j=j_2+1}^{n_2} |\, a'_{ijtk}|^+ \mathrm{Sign}(a'^{+}_{ijtk}) y^{-}_{jtk} - V_{itk} \leqslant w^{+}_{itk} - \lambda^-(w^{+}_{itk} - w^{-}_{itk}), \quad \forall i, t;\ k = 1, 2, \ldots, K_t \tag{14d}$$

$$V_f + \sum_{r=1}^{m_1}\sum_{t=1}^{T} V_{rt} + \sum_{i=1}^{m_2}\sum_{t=1}^{T}\sum_{k=1}^{K_t} V_{itk} \leqslant TV \tag{14e}$$

$$x^{+}_{jt} \geqslant x^{-}_{jtopt}, \quad \forall t;\ j = 1, 2, \ldots, j_1 \tag{14f}$$

$$0 \leqslant x^{-}_{jt} \leqslant x^{+}_{jtopt}, \quad \forall t;\ j = j_1+1, j_1+2, \ldots, n_1 \tag{14g}$$

$$y^{+}_{jtk} \geqslant y^{-}_{jtkopt}, \quad \forall t;\ j = 1, 2, \ldots, j_2;\ k = 1, 2, \cdots, K_t \tag{14h}$$

$$0 \leqslant y^{-}_{jtk} \leqslant y^{+}_{jtkopt}, \quad \forall t;\ j = j_2+1, j_2+2, \ldots, n_2;\ k = 1, 2, \ldots, K_t \tag{14i}$$

$$0 \leqslant \lambda^- \leqslant 1 \tag{14j}$$

where V_f is a violation variable for the objective function; V_{rt} and V_{itk} are two sets of violation variables for the constraints; and TV is the total tolerable violation limit. When $TV = 0$, model (14) is the second submodel of IFMP, where the goal and constraints will not be violated. However, when $TV > 0$, the corresponding constraint of model (8) is allowed to be relaxed, associated with a given risk level of constraint-violation. Therefore, the model's decision space can be expanded through introduction of a number of violation variables. With varied violation levels, a variety of solutions associated with different λ^- values will be generated, corresponding to different constraint-violation risks. They will be useful for analyzing tradeoffs among the system cost, satisfaction degree, and constraint-violation risk.

Appendix 2. Nomenclatures for variables and parameters

$f^{\pm}$	expected system cost for waste management (CAN$)
i	type of waste management facility, with $i = 1$ for landfill, $i = 2$ for composting facility, and $i = 3$ for recycling facility
t	time period, $t = 1, 2, \ldots, T$
L_t	length of time period t *(week)*
$DP^{\pm}_{it}$	operating cost of facility i for excess waste flow during period t *(CAN$/tonne)*
$DR^{\pm}_{it}$	collection and transportation cost for excess waste flow from the city to facility i during period t *(CAN$/tonne)*
$DT^{\pm}_{it}$	transportation cost for excess waste residue from facility i to the landfill during period t (CAN$/tonne), $i = 2, 3$
$FE^{\pm}_{i}$	residue flow rate from facility i to the landfill (where the composting and recycling facilities generate residues of [7,8]% and [8,10]% on their mass bases of the incoming waste streams, respectively), $i = 2, 3$
$FT^{\pm}_{it}$	transportation cost for residue flow from facility i to the landfill during period t (CAN$/tonne), $i = 2, 3$
$FLC^{\pm}_{1t}$	fixed-charge cost for landfill expansion in period t (CAN$$10^6$)
$FTC^{\pm}_{it}$	fixed-charge cost for the development and/or expansion of composting and recycling facilities in period t (CAN$$10^6$)
$LC^{\pm}$	existing landfill capacity (tonne)
$M^{\pm}_{itk}$	amount by which the pre-regulated waste flow level ($T^{\pm}_{it}$) is exceeded when the waste-generation rate is $WG^{\pm}_{tk}$ with probability p_{tk} under scenario k (tonne/week) (recourse decision variables)
$N^{\pm}_{itk}$	variable upper bound for the expanded capacity in period t under scenario k (m^3 or tonne/week)
$OP^{\pm}_{it}$	operating cost of facility i for pre-regulated waste flow during period t (CAN$/tonne)
p_{tk}	probability of occurrence for waste-generation in period t under scenario k
K_t	number of waste-generation scenarios in district j in period t
$RE^{\pm}_{it}$	revenue from composting and recycling facilities during period t (CAN$/tonne), $i = 2, 3$
$RM^{\pm}_{it}$	revenue from composting and recycling facilities because of excess flow during period t (CAN$/tonne), $i = 2, 3$
$TC^{\pm}_{i}$	existing capacity of composting and recycling facilities (tonne/week), $i = 2, 3$
$TR^{\pm}_{it}$	collection and transportation cost for pre-regulated waste flow from the city to facility i during period t *(CAN$/tonne)*
T_{it}	pre-regulated waste flow to facility i during period t (tonne/week) (first-stage decision variables)
$T_{ijt\min}$	minimum pre-regulated waste flow to facility i during period t *(tonne/week)*
$T_{ijt\mathrm{Max}}$	maximum pre-regulated waste flow to facility i during period t *(tonne/week)*
V_{LC}	violation level for the constraint of landfill capacity under different scenarios (%)
V_{TC2}	violation level for the constraint of composting facility capacity (%)
V_{TC3}	violation level for the constraint of recycling facility capacity (%)
V_{WG}	violation level for the constraint of waste-disposal demand under different scenarios (%)
V_{DG}	violation level for the constraint of waste diversion requirement (%)
$VLC^{\pm}_{1t}$	variable cost for landfill expansion in period t (CAN$/tonne)
$VTC^{\pm}_{it}$	variable cost for the development and/or expansion of composting and recycling facilities in period t *(CAN$/tonne)*
$WG^{\pm}_{tk}$	amount of waste generated in the city in period t under scenario k *(tonne/week)*
$X^{\pm}_{itk}$	decision variables for capacity expansion/development of facility i in period t under scenario k (tonne or tonne/week)
$Y^{\pm}_{itk}$	binary variables for identifying whether facility i needs to be developed and/or expanded in period t under scenario k

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