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DIPIP: Dual Interval Probabilistic Integer Programming for Solid Waste Management

Z. F. Liu[1], G. H. Huang[1,2,*], R. F. Liao[1], and L. He[3]

[1]*Environmental Systems Engineering Program, Faculty of Engineering, University of Regina, Regina, Saskatchewan S4S 0A2, Canada*
[2]*Chinese Research Academy of Environmental Science, North China Electric Power University, Beijing, 100012-102206, China*
[3]*Department of Civil Engineering, Ryerson University, Toronto, Ontario, Canada*

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ABSTRACT. In this study, a dual interval probabilistic integer programming (DIPIP) model is developed for long-term planning of solid waste management systems under uncertainty. Methods of joint probabilistic programming and dual interval analysis are introduced into an interval-parameter mixed-integer linear programming framework. DIPIP improves upon the existing interval, chance-constrained and joint probabilistic programming approaches by allowing system uncertainties expressed as probability distributions as well as single and dual intervals. Highly uncertain information for the lower and upper bounds of interval parameters can be reflected. The developed method is applied to a case study of solid waste management. The results indicate that reasonable solutions of facility expansion schemes and waste-flow allocation patterns have been generated. A tradeoff exists between economic consideration and system stability.

Keywords: decision making, dual interval, environment, joint probabilistic, solid waste, uncertainty

1. Introduction

Effective planning of solid waste management systems is important in facilitating sustainable urban development. Environmental protection and resources conservation are of major concerns along with increasing waste generation and decreasing waste-disposal capacity. In response to these, various optimization techniques were used for supporting effective management of the systems (Chang and Wang, 1997; Huang et al., 2007; Ahluwalia and Nema, 2007; Li, 2007; He et al., 2008). At the same time, uncertainties exist in many system components (e.g. random waste generation rates, fluctuating disposal capacities) and their complex interactions, and thus affect the relevant decision.

During the past decades, many efforts were made for dealing with uncertainties in municipal solid waste (MSW) management. They were mainly related to stochastic, fuzzy and interval mathematical programming methods (abbreviated as SMP, FMP and IMP). SMP and FMP would tackle probabilistic and possibilistic uncertainties, respectively; IMP could deal with uncertainties expressed as interval numbers, when distribution or membership information was unavailable (Lee et al., 1991; Chanas and Zielinski, 2000; Li, 2003; Huang et al., 1992, 1994, 1995; Chang and Lu, 1997; Chi and Huang, 1998; Yeomans and Huang, 2003; Yeomans et al., 2003; Wang, 2007). Compared with SMP and FMP, the IMP method had advantages in allowing uncertainties to be directly conveyed into the optimization processes and resulting solutions without complex intermediate transformations.

Meanwhile, several integrated IMP and SMP methods were developed to handle problems with their right-hand-side coefficients being highly uncertain. For example, Maqsood and Huang (2003) introduced a two-stage interval-stochastic programming (TISP) model for the planning of solid waste management systems under uncertainty. Li (2004) improved on the TISP model through considering dynamic analysis for disposal-capacity expansion, and thus proposed interval two-stage mixed-integer linear programming (ITMILP) model. In their studies, stochastic problems were tackled by two-stage stochastic programming (TSP) method within an IMP framework. In fact, the problems could also be handled through the chance-constrained programming (CCP) method. For example, a hybrid inexact chance-constrained mixed-integer linear programming (ICCMILP) method was proposed by Liu et al. (2000) for nonrenewable energy resources management under uncertainty. Huang et al. (2001) developed an interval-parameter fuzzy-stochastic programming model and applied it to the planning of a MSW management system, where methods of CCP and FMP were incorporated within a general interval-parameter mixed-integer linear programming framework.

Although CCP can reflect the reliability of satisfying individual system constraints, it may encounter difficulties in analyzing interactions among multiple constraints, which are to be satisfied at a joint probability level. For example, waste ge-

* Corresponding author. Tel.: +1 306 5854095; fax: +1 306 5854855.
E-mail address: gordon.huang@uregina.ca (G. H. Huang).

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neration rates in multiple cities each may be at high or low levels. They are required to be satisfied at a probability level, in case the waste generation rates are unacceptably high at the same time (leading to overflow at receiving facilities). Such complexities can be tackled through joint probabilistic constraint programming (JPC) method (Miller and Wagner, 1965; Prekopa, 1970, 1971, 1993, 1995; Beavis and Dobbs, 1990; Mayer, 1992; Kall and Wallace, 1994). In addition, integration of IMP and SMP is based on known distributional information for random coefficients and/or known lower and upper bounds of interval parameters. However, in many real-world problems, the bounds of interval parameters could also be uncertain. For example, estimates of the waste transportation costs among transfer stations may roughly be $[*a*, *c*] to $[*d*, *b*] as a result of queuing delays, traffic congestions and/or other emergent events. This leads to the presence of dual uncertainties, which can be expressed as dual intervals (e.g. [[*a*, *c*], [*d*, *b*]]).

Therefore, incorporation of the joint probabilistic constraint programming (JPC) method and the dual-interval concept within an interval linear programming framework would be helpful for reflecting such dual uncertainties. Although several approaches were reported on dealing with uncertainties in the boundaries of interval inputs (Cai et al., 2007; Nie et al., 2007; Guo et al., 2008; Lu et al., 2008; He et al., 2008), limitations existed when the quality of information was not satisfactory enough to be presented as probability and/or possibility distributions for the boundaries. Few previous reports could be found on the development of a hybrid inexact probabilistic model that can simultaneously handle joint probabilistic constraints and dual uncertainties.

The objective of this study is to develop a dual interval probabilistic integer programming (DIPIP) approach and apply it to municipal solid waste management. The developed DIPIP method is formulated by incorporating the concepts of dual intervals, joint-probabilistic constraint programming (JPP) and mixed-integer linear programming (MIP) within a general framework. The DIPIP has advantages in exhibiting imprecision via intervals and randomness via probabilities. Its applicability will be demonstrated through a case study of MSW management planning.

2. Development of the DIPIP Model

Consider random coefficients in the right-hand side (B) in a linear programming (LP) problem. The problem can be formulated as follows (Charnes and Cooper, 1965):

$$\text{Min } C\,X \tag{1a}$$

subject to:

$$\text{P}(AX \geq B) \geq 1 - q \tag{1b}$$

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

where B may have all their elements as random variables, which are assumed to be uncorrelated; $1 - q$ is a probability the constraint should be satisfied with, and q is the admissible risk of violating the constraint. If the entire set of constraints in (1b) are required to be satisfied with at least a joint probability level of $1 - q$, a JPC model can be formulated as follows (Miller and Wager, 1965):

$$\text{Min } C\,X \tag{2a}$$

subject to:

$$\text{P}(A_i\,X \geq b_i,\ i = 1, \ldots, \text{r}) \geq 1 - q \tag{2b}$$

$$A_t\,X \geq b_t,\ t \neq i \tag{2c}$$

$$X \geq 0 \tag{2d}$$

where the random variables are independent of each other; q is the admissible risk of violating the entire set of constraints. To solve the problem, Lejeune and Prekopa (2005) proposed an approximation scheme by replacing the JPC model with a set of individual constraints and reinforcing the requirements in the above model. Model (2) can be rewritten as follows (Lejeune and Prekopa, 2005):

$$\text{Min } C\,X \tag{3a}$$

subject to:

$$A_i x \geq b_i^{q_i},\ i = 1,\ 2,\ \ldots,\ r \tag{3b}$$

$$\sum_{i=1}^{r}(q_i) \leq q \tag{3c}$$

$$A_t\,X \geq b_t,\ t \neq i \tag{3d}$$

$$X \geq 0 \tag{3e}$$

where $b_i^{(qi)} = F_{\text{i}}^{-1}(q_i)$, given the cumulative distribution function of b_i, and the probability of violating constraint i (q_i). The problem with (3) is that the left-hand side coefficients and the objective functions are deterministic. In fact, the available information in many practical problems is not satisfactory enough to access probability distributions, as planners and engineers typically find it more difficult to specify distributions than to define fluctuation ranges. Thus, to address this, one potential approach is through the introduction of interval parameter programming method into the above JPC framework, considering continuous and binary variables. This produces an interval-parameter probabilistic integer programming (IPIP) model as follows (Huang et al., 1992, 1995):

$$\text{Min } C^{\pm}\,X^{\pm} \tag{4a}$$

subject to:

$$\text{P}(A_i^{\pm} X^{\pm} \geq b_i, i = 1,\ \ldots,\ r) \geq 1 - q\ ,\ r \in M,\ r \neq t \tag{4b}$$

$$A_t^{\pm} X \geq b_t^{\pm},\ t \neq i \quad (4c)$$

$$X^{\pm} \geq 0 \text{ or integer} \quad (4d)$$

where $A^{\pm} \in \{R^{\pm}\}^{m\times n}$, $b_t^{\pm} \in \{R^{\pm}\}^{m\times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1\times n}$, $X^{\pm} \in \{R^{\pm}\}^{n\times 1}$, and $R^{\pm}$ means a set of interval numbers; the "−" and "+" superscripts represent lower and upper bounds of the interval parameters or variables, respectively. In the solution process, the IPIP model can be transformed into two deterministic submodels, corresponding to the lower and upper bounds of the desired objective; the two submodels will then be solved sequentially (Huang et al., 1992, 1995).

In model (4), uncertain inputs are expressed as probability distributions and intervals (with crisp lower and upper bounds). In many cases, the two bounds of the input intervals (e.g., *a* and *b* for interval [*a*, *b*]) may be uncertain and associated with various impact factors such that the crisp values may be unavailable. This leads to the presence of dual uncertainties. One potential way of describing such uncertainties is through the introduction of the concept of dual intervals (expressed as [[*a*, *c*], [*d*, *b*]]) (Joslyn, 2003; Liu et al., 2009). The dual intervals are interval-boundary intervals, where lower and upper bounds are expressed as intervals (i.e., [*a*, *c*] and [*d*, *b*], respectively). To interpret such dual intervals, a method was proposed by Joslyn (2003) through an equivalence class of random intervals. The detailed elicitation algorithm can be found in the papers of Joslyn (2003) and Liu et al. (2009). For dual uncertainties in cost/revenue parameters in the objective function, an extended consideration is the incorporation of the dual-interval concept into the IPIP framework, producing a dual interval probabilistic integer programming (DIPIP) model as follows:

$$\text{Min } [C^{\pm}]^{\pm} X^{\pm} \quad (5a)$$

subject to:

$$P(A_i^{\pm} X^{\pm} \geq b_i,\ i = 1, \ldots, r) \geq 1 - q,\quad r \in M, r \neq t \quad (5b)$$

$$A_t^{\pm} X^{\pm} \geq b_t^{\pm},\quad t \in M, t \neq r \quad (5c)$$

$$X^{\pm} \geq 0 \quad \text{or integer} \quad (5d)$$

where $[C^{\pm}]^{\pm} \in \{R^{\pm}\}^{1\times n}$, and $R^{\pm}$ means a set of dual intervals. In addition, $1 - q$ is a pre-regulated parameter, imposing that a set of constraints are satisfied with at least a joint probability of $1 - q$.

Solutions for the DIPIP model are based on the transformation of random and single/dual interval inputs. With a minimized objective function, each joint probabilistic constraint will be first substituted by a set of individual constraints through the preceding approximation scheme. Second, a class of random intervals (interval-valued random variables) can be derived or simulated from dual intervals (e.g. [[*a, c*], [*d, b*]]), according to information from the dual intervals, as provided by decision makers (Joslyn, 2003; Liu et al., 2009). The mean value of such random intervals is then obtained. Thirdly, the DIPIP model will be solved through the interactive algorithm of Huang et al. (1992, 1995).

3. Application to Solid Waste Management

3.1. Overview of the Study System

A hypothetical system is considered to demonstrate applicability of the DIPIP method for solid waste management, where the technical data are based on the MSW management literature (Baetz, 1990; Huang et al., 1992, 2001). In the system, three periods (5 years for each) are considered in a 15-year planning horizon. There are three MSW management facilities [an existing landfill and two waste-to-energy (WTE) facilities] available for three cities (as shown in Figure 1), where cities 2 and 3 are developing and city 1 is an overdeveloped site. The landfill has an existing capacity of 2.75 to 3.05 × 10^6 tonne. Residues from the facilities will be shipped to the landfill directly. Revenues from their energy sales are approximately $15 to $25 per tonne of waste treated.

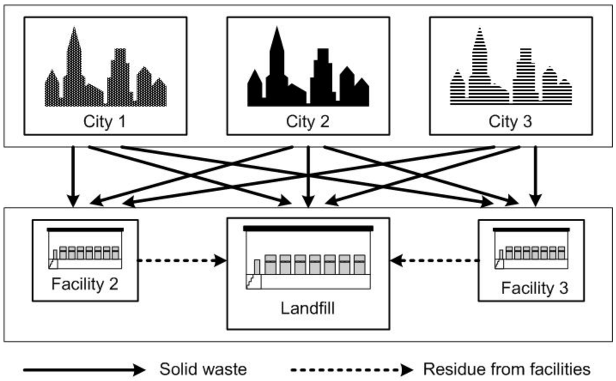

Figure 1. Overview of the study system.

Over the planning horizon, the WTE facilities can adopt any of the three expansion options in each of the three time periods (Table 1). The Table also shows capital costs of capacity expansions for the WTE facilities. Table 2 contains waste generation rates in the three cities, with an assumption of known normal distributions for the random generation rates in cities 2 and 3. In addition, as rapid economic development is taking place in cities 2 and 3, their waste generation rates may be high at the same time. Thus, the waste from both cities must be handled at a joint probability level of 95% over the entire planning horizon. Table 3 shows operation costs of the three facilities and transportation costs for shipping waste from the city to the facilities. Table 4 lists costs for residue transportation from the WTE facilities to the landfill, which are represented as dual intervals, accounting for the effects of queuing delay and variations of the energy price. Suppose the outer-layer values of the dual intervals could receive more confidence from decision makers. According to the elicitation algorithm, the dual intervals can be transformed into a series

Table 1. Capacity Expansion Options and Their Costs for WTE Facilities

	Time period		
	k = 1	k = 2	k = 3
Capacity expansion for WTE facilities, i = 2, 3 (t/day)			
Option 1	50	50	50
Option 2	100	100	100
Option 3	150	150	150
Capital cost of WTE facility expansion, i = 2, 3 ($\$10^6$)			
Option 1	10.5	8.3	6.5
Option 2	15.2	11.9	9.3
Option 3	19.8	15.5	12.2

Table 2. Waste Generation Rates

	Time period		
	k = 1	k = 2	k = 3
Waste generation rate (t/day)			
City 1	[175, 225]	[200, 250]	[225, 275]
City 2	$N(300, 10^2)$	$N(350, 10^2)$	$N(400, 10^2)$
City 3	$N(300, 20^2)$	$N(300, 20^2)$	$N(350, 20^2)$

of random intervals (Liu et al.,2009). Generally, the rates of waste generation and the costs for waste transportation and treatment/disposal may vary temporally and spatially. The problem under consideration is how to effectively allocate the waste flows (subjected to a class of environmental, economic, treatment/disposal and technical constraints) from the city to the facility and minimize the overall system cost. A DIPIP model for the study system can then be formulated.

3.2. DIPIP Model for Solid Waste Management

$$\text{Min}\, f^{\pm} = 1825 \cdot \sum_{j=1}^{3}\sum_{k=1}^{3}\{\sum_{i=1}^{3} x_{ijk}^{\pm} \cdot (TR_{ijk}^{\pm} + OP_{ik}^{\pm}) + \sum_{i=2}^{3} x_{ijk}^{\pm} \cdot [FE^{\pm} \cdot ([FT_{ik}^{\pm}]^{\pm} + OP_{ik}^{\pm}) - RE_{ik}^{\pm}]\} + \sum_{i=2}^{3}\sum_{m=1}^{3}\sum_{k=1}^{3} FTC_{imk}^{\pm} Z_{imk}^{\pm} \quad (10a)$$

subject to:

$$1825 \cdot \sum_{j=1}^{3}\sum_{k=1}^{3} (x_{1jk}^{\pm} + \sum_{i=2}^{3} x_{ijk}^{\pm} \cdot FE^{\pm}) \le TL^{\pm} \quad (10b)$$

(Landfill capacity constraint)

$$\sum_{j=1}^{3} x_{2jk}^{\pm} \le TE_2^{\pm} + \sum_{k=1}^{3}\sum_{m=1}^{3} \Delta TE_{2mk}^{\pm} Z_{2mk}^{\pm}, \quad \forall j \quad (10c)$$

(WTE facility 2 capacity constraints)

Table 3. Transportation and Operation Costs

	Time period		
	k = 1	k = 2	k = 3
Cost of transportation to landfill ($/t)			
City 1	[12.1, 16.1]	[13.3, 17.7]	[14.6, 19.5]
City 2	[10.5, 14.0]	[11.6, 15.4]	[12.8, 16.9]
City 3	[12.7, 17.0]	[14.0, 18.7]	[15.4, 20.6]
Cost of transportation to WTE facility 2 ($/t)			
City 1	[9.6, 12.8]	[10.6, 14.1]	[11.7, 15.5]
City 2	[10.1, 13.4]	[11.1, 14.7]	[12.2, 16.2]
City 3	[8.8, 11.7]	[9.7, 12.8]	[10.6, 14.0]
Cost of transportation to WTE facility 3 ($/t)			
City 1	[12.1, 16.1]	[13.3, 17.7]	[14.6, 19.5]
City 2	[12.8, 17.1]	[14.1, 18.8]	[15.5, 20.7]
City 3	[4.5, 5.6]	[4.6, 6.2]	[5.1, 6.8]
Operation cost ($/t)			
Landfill	[30, 45]	[40, 60]	[50, 80]
WTE facility 1	[55, 75]	[60, 85]	[65, 95]
WTE facility 2	[55, 70]	[60, 80]	[65, 85]

Table 4. Cost of Residue Transportation from the WTE Facilities to the Landfill ($/t)

	Time period		
	k = 1	k = 2	k = 3
From WTE facility 2 to the landfill	[[4.5, 4.8], [6.1, 6.4]]	[[5, 5.3], [7.4, 7.7]]	[[5.5, 5.8], [7.4, 7.7]]
From WTE facility 3 to the landfill	[[13.1, 13.5], [17.6, 18]]	[[14.4, 14.8], [19.4, 19.8]]	[[15.9, 16.3], [21.4, 21.8]]

$$\sum_{j=1}^{3} x_{3jk}^{\pm} \le TE_3^{\pm} + \sum_{k=1}^{3}\sum_{m=1}^{3} \Delta TE_{3mk}^{\pm} Z_{3mk}^{\pm}, \quad \forall j \quad (10d)$$

(WTE facility 3 capacity constraints)

$$\sum_{i=1}^{3} x_{i1k}^{\pm} \ge WG_{1k}^{\pm}, \quad \forall\, k \quad (10e)$$

(Waste disposal demand constraints)

$$\text{P}\left\{\begin{array}{l} \sum_{i=1}^{3} x_{i2k}^{\pm} \ge WG_{2k}^{\pm} \\ \sum_{i=1}^{3} x_{i3k}^{\pm} \ge WG_{3k}^{\pm} \end{array}\right\} \ge 1 - q_k, \quad \forall\, k \quad (10f)$$

(Waste disposal demand constraints)

Table 5. System Costs under Different Scenarios with Different Combined q_{jt} Levels

$f^{\pm}$(10^6)	Scenario 1	Scenario 2	Scenario 3	Scenario 4
$WG_3 \backslash WG_2$	q_{21} = 0.001	q_{22} = 0.005	q_{23} = 0.010	q_{24} = 0.025
q_{31}=0.025	[286.99, 532.22]	[286.90, 532.01]	[286.80, 531.80]	[286.51, 531.17]
q_{32}=0.010	[287.61, 533.40]	[287.51, 533.19]	[287.40, 532.98]	[287.11, 532.35]
q_{33}=0.005	[287.82, 533.80]	[287.72, 533.59]	[287.62, 533.43]	[287.31, 532.74]
q_{34}=0.001	[288.03, 534.19]	[287.93, 533.98]	[287.83, 533.77]	[287.52, 533.14]

$$Z_{imk}^{\pm} \begin{cases} \leq 1 \\ \geq 0 \\ \text{integer} \quad i = 2,\ 3;\ \forall\ m,\ k \end{cases} \tag{10g}$$

(Non-negativity and binary constraints)

$$\sum_{m=1}^{3} Z_{imk}^{\pm} \leq 1, \quad i = 2,\ 3, \quad \forall\ k \tag{10h}$$

(WTE facilities expansion may occur in any given time period)

$$x_{ijk}^{\pm} \geq 0\ ,\ \forall\ \text{i}, j, k \tag{10i}$$

(Non-negativity constraints)

where:

$FE^{\pm}$ residue flow from the waste-to-energy facility to the landfill (% of incoming mass to waste-to-energy facility);

$[FT_{ik}^{\pm}]^{\pm}$ transportation costs of waste flow from the waste-to-energy facility to the landfill in period k ($/t);

$FTC_{imk}^{\pm}$ capital cost of expanding waste treatment facility i by option m in period k ($/t), and i = 2, 3;

$OP_{ik}^{\pm}$ operating costs of facility i in period k ($/t);

$RE_k^{\pm}$ revenue from the waste-to-energy facility in period k ($/t);

$TE_{ik}^{\pm}$ maximum capacity of the waste-to-energy facility (t/day);

$TL^{\pm}$ capacity of the landfill (t);

$TR_{ijk}^{\pm}$ transportation costs from city j to facility i during period k ($/t);

$WG_{jk}^{\pm}$ waste generation rate in city j to facility i during period k (t/day);

$x_{ijk}^{\pm}$ waste flow rate from city j to facility i in period k (t/day), i = 1, 2, 3; j = 1, 2, 3; k = 1, 2, 3;

i index for facility (i = 1 for the landfill, and i = 2, 3 for the waste-to-energy facility);

j index for the three cities (j = 1, 2, 3);

k index for the time period (k = 1, 2, 3);

$1 - q_k$ joint probability level during period k;

$Z_{imk}^{\pm}$ binary decision variable for treatment facility i with expansion option m at the start of period k, and i = 2, 3;

$\Delta TE_{imk}^{\pm}$ level of capacity expansion option m for facility m at the start of period k (t/day), and i = 2, 3.

3.3. Result Analysis

Table 5 presents the solution for system cost, obtained through the DIPIP model , under different scenarios with given q_{jt} levels (j = 2, 3; t = 1, 2, …, 4, where j is an index for the cities and t is for the scenarios). A series of solutions (16 sets) under different combinations of q_{jt} levels can be obtained (with a joint probability level of 95% in terms of satisfying waste disposal needs in cities 2 and 3). Four scenarios (when q_{21} = 0.001, q_{22} = 0.005, q_{23} = 0.010, and q_{24} = 0.025, respectively) are inves- tigated and each is embedded with four sub-scenarios. Analysis of the modeling solutions (when q_{31} = 0.025, and q_{21} = 0.001, q_{22} = 0.005, q_{23} = 0.010, q_{24} = 0.025) are provided below, with local minimum-costs.

For the facility expansion, there is no difference between the schemes under the four scenarios. Facility 2 would adopt an expansion scheme of [0, 50] t/day in period 2, and facility 3 would have an increment of [0, 100] t/day in period 1. It means that when the decision scheme tends toward f^- under advantageous conditions, no expansion would exist; however, facilities 2 and 3 would adopt expansion schemes of 50 and 100 t/day under demanding conditions (f^+), respectively.

As for waste flow allocation solutions (Table 6), a similarity can be found under the four scenarios. City 1 would ship a large portion of its waste to the landfill, and divert the rest to the WTE facilities due to its close proximity. Waste from city 2 would be mainly allocated to the landfill and facility 2, while waste from city 3 would be mostly shipped to facility 3 due to an apparent closeness effect. For example, under scenario 1, city 1 would ship [140, 157.5], 35 and [0, 32.5] t/day waste in period 1 to the landfill, facility 2 and 3, respectively. Waste from city 2 to the landfill and facility 2 in period 1 would be 264 and [66, 90] t/day, respectively. Waste from city 3 in period 1 to facility 3 and the landfill would be 275 and 82 t/day, respectively. In addition, the system costs under the four scenarios would be $[286.99, 532.22] ×$10^6$, $[286.90, 532.01] × 10^6, $[286.80, 531.80] × 10^6 and $[286.51, 531.17] × 10^6, respectively. They would vary under different waste flow allocation patterns. Adjusting waste flows could reflect variations of system conditions due to the existence of uncertainties. In addition, the q_{jt} levels represent probabilities at which the constraints are violated. A raised q_{jt} level implies an increased risk of constraint violation (i.e. a decreased strictness for the constraints, and thus an expanded decision space). A higher q_{jt} level would correspond to a lower system cost, but it may not guarantee environmental regulations and waste management requirements are met. In comparison, under a lower q_{jt} level, the requirements would be met (at a higher system cost due to a higher waste generation rate).

Replacing the JPC with the CCP, the study problem would

Table 6. Solutions of the DIPIP and DICCIP Models

Waste flow (t/day)	Facility i	City j	Period k	Models	
				Scenario 1 (DIPIP)	DICCIP
$X_{111}^{\pm}$	1	1	1	[140, 157.5]	[140, 157.5]
$X_{112}^{\pm}$	1	1	2	[160, 175]	[160, 175]
$X_{113}^{\pm}$	1	1	3	[180, 192.5]	[180, 192.5]
$X_{121}^{\pm}$	1	2	1	264	261.6
$X_{122}^{\pm}$	1	2	2	304	301.6
$X_{123}^{\pm}$	1	2	3	344	341.6
$X_{131}^{\pm}$	1	3	1	82	79
$X_{132}^{\pm}$	1	3	2	51.8	73.3
$X_{133}^{\pm}$	1	3	3	113	109.4
$X_{211}^{\pm}$	2	1	1	35	35
$X_{212}^{\pm}$	2	1	2	40	40
$X_{213}^{\pm}$	2	1	3	45	45
$X_{221}^{\pm}$	2	2	1	[66, 90]	[65.4, 90]
$X_{222}^{\pm}$	2	2	2	[76, 104.8]	[75.4, 79.4]
$X_{223}^{\pm}$	2	2	3	[86, 91.5]	[85.4, 90.6]
$X_{231}^{\pm}$	2	3	1	0	0
$X_{232}^{\pm}$	2	3	2	30.2	5.7
$X_{233}^{\pm}$	2	3	3	19	19.6
$X_{311}^{\pm}$	3	1	1	[0, 32.5]	[0, 32.5]
$X_{312}^{\pm}$	3	1	2	[0, 35]	[0, 35]
$X_{313}^{\pm}$	3	1	3	[0, 37.5]	[0, 37.5]
$X_{321}^{\pm}$	3	2	1	[0, 9]	[0, 8.1]
$X_{322}^{\pm}$	3	2	2	[0, 9.2]	[0, 33.8]
$X_{323}^{\pm}$	3	2	3	[0, 37.5]	[0, 37.5]
$X_{331}^{\pm}$	3	3	1	275	275
$X_{332}^{\pm}$	3	3	2	275	275
$X_{333}^{\pm}$	3	3	3	275	275
$f^{\pm}$ ($\$10^6$)				[286.99, 532.22]	[285.02, 526.59]

then be formulated as a dual interval chance-constrained integer programming (DICCIP) model. The random waste generation rates in cities 2 and 3 will each be treated at a probability level of 0.95 (instead of at a joint probability of 0.95 in the DIPIP problem). This implies there would be an increased chance of the constraints being violated from a probability of 0.05 all of the time (under the JPC) to 0.05 each time (under the CCP). The increased chance of constraint violation would correspond to a lower cost due to a decrease in the projected waste generation rates, but it may mean a reduced probability for satisfying environmental regulations and waste management requirements.

Table 6 also shows the solutions from the DICCIP model. They are different from those obtained through the DIPIP model. Facility 2 would adopt an expansion scheme of [0, 50] t/day in period 3, and facility 3 would have an increment of [0, 100] t/day in period 1. Facility 2 would be expanded in period 3 is because the management capacity would be higher than that from the DIPIP model (due to the increased chance of constraint violation). Cities 1 and 2 would ship more waste to the landfill and less to the other two facilities. City 3 would divert a portion of its waste from facility 3 to the landfill and facility

2. The system cost would be \$[285.02, 526.59] × 10^6, which is less than that from the DIPIP model.

Generally, solutions from the DICCIP present a preference of shipping the waste to the landfill. The system is in a more risky condition (with a raised chance of overloaded waste flows). In other words, the plan, based on the DIPIP solution, is more reliable than that of the DICCIP solution. In DIPIP, the risk of constraint violation is lower than a joint level. It addresses a situation where the waste generation rates in cities 2 and 3 could be unacceptably high at the same time (leading to overflow at receiving facilities). Capable of providing a desired compromise between economic consideration and system stability, the DIPIP would be more realistic in reflecting the system complexity. The main advantage of DIPIP is its joint consideration of multiple interactive conditions for satisfying the constraints. Due to its capacity for reflecting dual uncertainties, the DIPIP is capable of providing more robust solutions.

4. Conclusions

A dual interval probabilistic integer programming (DIPIP) method has been developed for MSW management planning. The method improves upon the existing probabilistic programming and integer programming approaches by incorporating the concept of dual intervals within the optimization framework. The DIPIP addresses system uncertainties expressed as probability distributions and single, dual intervals. It can effectively reflect highly uncertain information for boundaries of the input intervals and system dynamics. The DIPIP can jointly consider multiple interactive conditions for satisfying the constraints and be more realistic in reflecting the system complexity. The obtained interval solutions can be used to generate decision alternatives.

To demonstrate applicability of the method, a hypothetical planning problem has been employed regarding waste management facility expansion and waste flow allocation within a MSW management system. The results indicate that reasonable solutions of facility expansion schemes and waste-flow allocation patterns have been generated. Tradeoffs between system cost and stability are analyzed. A willingness to pay higher operation costs will guarantee system reliabilities. However, a desire to reduce the costs will potentially run into system disruptions.

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References

Ahluwalia, P.K., and Nema, A.K. (2007). A goal programming based multi-time step optimal material flow analysis model for integrated computer waste management. *J. Environ. Inform.*, 10(2), 82-98.

Arey, M.J., and Baetz, B.W. (1993). Simulation modeling for the sizing of solid waste receiving facilities. *Can. J. Civil Eng.*, 20, 220-227.

Baetz, B.W. (1990). Capacity planning for waste management systems. *Civil Eng. Syst.,* 7, 229-235.

Beavis, B., and Dobbs, I. (1990). *Optimization and Stability Theory for Economic Analysis*, Cambridge, Cambridge University Press.

Cai, Y.P., Huang, G.H., Nie, X.H., Li, Y.P., and Tan, Q. (2007). Municipal solid waste management under uncertainty: A mixed interval parameter fuzzy-stochastic robust programming approach. *Environ. Eng. Sci.,* 24(3), 338-352.

Chanas, S., and Zielinski, P. (2000). On the equivalence of two optimization methods for fuzzy linear programming problems. *Eur. J. Oper. Res.,* 121(1), 56-63.

Chang, N.B., and Lu, H.Y. (1997). A new approach for long-term planning of solid waste management system using fuzzy global criterion. *J. Environ. Sci. Health*, A32(4), 1025-1047.

Chang, N.B., and Wang, S.F. (1997). A fuzzy goal programming approach for the optimal planning of metropolitan solid waste management systems. *J. Oper. Res.,* 32(4), 303-321.

Charnes, A., and Cooper, W.W. (1965). Deterministic equivalents for optimizing and satisfying under chance constraints. *Oper. Res.,* 11(1), 18-39.

Chi, G.F., and Huang, G.H. (1998). *Long-term planning of integrated solid waste management system under uncertainty*, University of Regina, Report submitted to the City of Regina, Saskatchewan, Canada.

Guo, P., Huang, G.H., He, L., and Sun, B.W. (2008). ITSSIP: Interval-parameter two-stage stochastic semi-infinite programming for environmental management under uncertainty. *Environ. Model. Software*, 23(12), 1422-1437.

He, L., Huang, G.H., Tan, Q., and Liu, Z.F. (2008). An interval full-infinite programming method to supporting environmental decision-making. *Eng. Optim.,* 40(8), 709-728.

Huang, G.H., Baetz, B.W., and Patry, G.G. (1992). A grey linear programming approach for municipal solid waste management planning under uncertainty. *Civil Eng. Sys.,* 9, 319-335.

Huang, G.H., Baetz, B.W., and Patry, G.G. (1994). Grey chance-constrained programming: Application to regional solid waste management planning," in *Effective Environmental Management for Sustainable Development, eds*. K.W. Hipel and L. Fang, Dordrecht: Kluwer Academic Publishers, The Netherlands, 267-280.

Huang, G.H., Baetz, B.W., and Patry, G.G. (1995). Grey integer programming: An application to waste management planning under uncertainty. *Eur. J. Oper. Res.,* 83, 594-620.

Huang, G.H., Sae-Lim, N., Liu, L., and Chen, Z. (2001). An interval-parameter fuzzy-stochastic programming approach for municipal solid waste management and planning. *Environ. Model. Assess.,* 6, 271-283.

Huang, G.H., Li, Y.P., Xiao, H.N., and Qin, X.S. (2007). An inexact two-stage quadratic program for water resources planning. *J. Environ. Inform.,* 10(2), 99-105.

Joslyn, C. (2003). Multi-interval elicitation of random intervals for engineering reliability analysis, in: *2003 Int. Symp. on Uncertainty Modeling and Analysis* (ISUMA 03).

Kall, P., and Wallace, S.W. (1994), *Stochastic Programming*, Chichester: Wiley, UK.

Lee, Y.W., Bogardi, I., and Stansbury, J. (1991). Fuzzy decision making in dredged-material management. *J. Environ. Eng.,* 117(2), 614-628.

Lejeune, M.A., and Prekopa, A. (2005). Approximations for and convexity of probabilistically constrained problems with random right-hand sides. *Ructor Rutgers Centre Oper. Res.,* RRR17-2005.

Li, J.B. (2003). Integration of stochastic programming and factorial design for optimal reservoir operation. *J. Environ. Inform.,* 1(2), 12-17.

Li, J.B. (2007). Stochastic risk assessment of groundwater contamination under uncertainty: A Canadian case study. *J. Environ. Inform.,* 9(2), 80-86.

Li, Y.P. (2004). *Development of an Inexact Two-Stage Mixed Integer Linear Programming Method for Solid Waste Management under Uncertainty*, M.Sc. Dissertation, Environmental Systems Engineering, University of Regina.

Liu, L., Huang, G.H., Fuller, G.A., Chakma, A., and Guo, H.C. (2000). A dynamic optimization Aapproach for non-renewable energy resources management in a regional system under uncertainty. *J. Petroleum Sci. Eng.,* 26(1), 301-310.

Liu, Z.F., Huang, G.H., Nie, X.H., and He, L. (2009). Dual interval linear programming model and its application to slid waste management planning. *Environ. Eng. Sci.,* 26(6), 1033-1045.

Lu, H.W., Huang, G.H. Liu, Z.F., and He, L. (2008). GHG-mitigation -induced rough-interval programming for municipal solid waste management. *J. Air & Waste Manage. Assoc.,* 58, 1546-1559.

Maqsood, I., and Huang, G.H. (2003). A two-stage interval-stochastic programming model for waste management under uncertainty. *J. Air & Waste Manage. Associ.*, 53, 540-552.

Mayer, J. (1992). Computational techniques for probabilistic constrained optimization problems, in K. Marti (Ed.), *Stochastic Optimization: Numerical Methods and Technical Applications*, Springer, Berlin, pp. 141-163.

Miller, B.L., and Wager, H.M. (1965). Chance constrained programming with joint constraints. *Oper. Res.,* 13(6), 930-945.

Nie, X.H., Huang, G.H., Li, Y.P., and Liu, L. (2007). IFRP: A hybrid interval-parameter fuzzy robust programming approach for waste management planning under uncertainty. *J. Environ. Manage.,* 84(1), 1-11.

Prekopa, A. (1970). On probabilistic constrained programming. *Mathe. Program. Study,* 28, 113-138.

Prekopa, A. (1971). Logarithmic concave measures with applications to stochastic programming. *Acta Scientiarum Mathematicarum,* 32, 301-315.

Prekopa, A. (1993). *Programming under Probabilistic Constraint and Maximizing A Probability under Constraints*, Report No. 35-93, Center for Operational Research, Rutgers University.

Prekopa, A. (1995). *Stochastic Programming: Mathematics and its Applications*, Dordrecht, Kluwer Academic Publishers.

Wang, X. (2007). Environmental informatics for environmental planning and management. *J. Environ. Inform.,* 9(1), 1-3.

Yeomans, J.S., and Huang, G.H. (2003). An Evolutionary Grey, Hop, Skip, and Jump Approach: Generating Alternative Policies for the Expansion of Waste Management. *J. Environ. Inform.*, 1(1), 37-51.

Yeomans, J.S., Huang, G.H., and Yoogalingam, R. (2003). Combining simulation with evolutionary algorithms for optimal planning under uncertainty: An application to municipal solid waste management planning in the regional municipality of Hamilton-Wentworth. *J. Environ. Inform.,* 2(1), 11-30.