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SRCCP: A stochastic robust chance-constrained programming model for municipal solid waste management under uncertainty

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ABSTRACT

A hybrid stochastic robust chance-constraint programming (SRCCP) model was developed in this study for supporting municipal solid waste management under uncertainty. The method improves upon the existing robust-optimization (RO) and chance-constraint programming (CCP) approaches by allowing analysis on trade-offs among expected value of the objective function, variation in the value of the objective function and the risk of violating constraints that contain uncertain parameters. SRCCP could be used to examine the balance between solution robustness and model robustness, and was especially useful for analyzing the reliability of satisfying (or risk of violating) system constraints under complex uncertainties. A long-term municipal solid waste management problem was used to demonstrate the applicability of SRCCP, with violations for capacity constraints being assumed under various significance levels. The study results demonstrated that a higher system cost may guarantee that waste-management requirements and environmental criteria be met, and a lower cost may lead to a higher risk of violating the related regulations. The proposed SRCCP model could be used by waste managers for identifying desired waste-management policies under various environmental, economic, and system-reliability constraints and complex uncertainties.

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1. Introduction

Municipal solid waste (MSW) management continues to be a major challenge for urban communities throughout the world (Huang and Chang, 2003). The rising MSW generation rates, increasing environmental and health concerns, shrinking waste-disposal capacities, and varying legislative and political conditions have significant impacts on selection of best waste-management practices (Li et al., 2007). Optimization models are effective tools for analyzing complex interrelationships among various system components, and provide decision supports for improving cost-effectiveness of waste-management strategies. However, MSW management is complicated with a variety of uncertainties that may be associated with waste generation, transportation, treatment and disposal processes. Such uncertainties could bring significant difficulties to the formulation of waste-management models and generation of effective solutions (Huang et al., 1993; Yeomans et al., 2003). It is thus desired that effective optimization models be advanced.

Previously, a large number of optimization methodologies have been proposed for dealing with uncertainties, such as fuzzy, stochastic, and interval programming methods (Kirca and Erkip, 1988; Zhu and Revelle, 1993; Chang and Wang, 1994, 1995, 1997; Leimbach, 1996; Li et al., 2007; Chang and Lu, 1997; Chang et al., 1997; Huang et al., 1992, 1993, 1994, 1995a,b, 2001, 2002, 2009; Chanas and Zielinski, 2000; Zeng et al., 2003, 2004; Zeng and Trauth, 2005; Qin et al., 2007a; Huang and Qin, 2008a,b). Among these approaches, the robust optimization (RO) is one of the stochastic programming methods that can bring risk aversion into optimization models and find robust solutions to environmental management problems (Mulvey et al., 1995). In a RO model, uncertain parameters, derived from noisy, incomplete, or erroneous data, are handled as random variables with discrete distributions. The major advantages of RO are (i) it integrates goal programming formulations with a scenario-based description of problem data, and generates a series of solutions that are progressively less sensitive to realizations of the model data from a scenario set (Mulvey et al., 1995); (ii) it is especially useful for helping decision makers evaluate trade-offs among the expected value of the objective function, variation in the value of the objective function and the risk of violating soft constraints or missing targets in the model. Over the past decade, RO models were used in many real-world applications, such as power capacity expansion, matrix balancing, air-force/airline scheduling, scenario immunization for financial planning, and

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minimum weight structural design (Yu and Li, 2000). Applications of RO in the environmental field were relatively limited. For example, Watkins and Mckinney (1997) applied RO to evaluate trade-offs among expected cost, cost variability, and system performance and reliability in water transfer planning and groundwater quality management, and control the effects of uncertainties. Leung et al. (2007) developed a robust-optimization model of a multi-site production planning problem for a multinational lingerie company in Hong Kong. The robustness and effectiveness of the developed model were demonstrated by numerical results, and the trade-off between solution robustness and model robustness was also analyzed.

However, the RO models also have a number of limitations. Firstly, as a discrete scenario-based approach, the complexities of RO would increase significantly as the amount of the designed scenarios increases (Mulvey et al., 1995). Since the number of scenarios is proportional to the number of stochastic variables, RO model can only tackle a limited number of uncertain parameters due to restrictions of extensive computational requirement. Secondly, the RO model assumes that the model robustness (i.e. feasibility robustness) is only related to the control constraints. In a RO model, the constraints are of two major types: structural and control constraints. The structural constraints are fixed and free of any noise, and they are similar to constraints in a deterministic model. The control constraints are subjected to noisy input data, and they are similar to constraints of a general model that contains uncertainties. However, in real-world applications, it is also possible that the structural constraints be subjected to an allowable level of violations in order to reduce the strictness of resource restrictions or environmental regulatory criteria. Such a violation may also be derived from uncertainties or disadvantageous system conditions. The conventional RO model cannot deal with such a complexity.

Chance-constrained programming (CCP) is another stochastic programming approach that can effectively reflect the reliability of satisfying (or risk of violating) system constraints under uncertainty. This method does not require that all of the constraints are strictly satisfied. Instead, they can be satisfied in a proportion of cases with given probabilities (Loucks et al., 1981). Many applications of CCP methods to environmental management problems were reported (Ellis et al., 1985, 1986; Morgan et al., 1993; Huang, 1998; Huang et al., 2001; Liu et al., 2003). For examples, Huang (1998) developed an inexact chance-constrained programming model for the water quality management within an agricultural system. Liu et al. (2000) developed a hybrid inexact chance-constrained mixed-integer linear programming method for non-renewable energy resources management under uncertainty, where the system objective was to maximize the economic return subject to constraints of resources availability and environmental regulations. Li et al. (2007) applied an inexact two-stage chance-constrained linear programming method for planning waste-management systems, where uncertainties were presented as both probability distributions and discrete intervals. These studies demonstrated that major advantages of CCP are (i) it could be used to convert a stochastic programming model into an equivalent deterministic version, and thus significantly reduce system complexities; (ii) it is especially useful for helping the decision makers make their decisions based on given probabilities of constraint violations; (iii) it could incorporate other uncertain optimization methods within a general framework. The above facts demonstrated that CCP possessed good practicability, and was easy to be integrated with other optimization methods.

Based on the above-mentioned facts, it is revealed that the RO is useful in analyzing the trade-offs among expected values of the objective function, variation in the value of the objective function and the risk of violating control constraints, but is weak in handling large-scenario problems and risk violations in structural constraints. CCP could be used to address risk violations for structural constraints with less intensive computational efforts, but is less capable of handling the trade-offs among multiple objectives. The two methods have varied strengths and weaknesses, with a potential for compensating each other when they are integrated within a general framework. Therefore, the objective of this research is to develop a stochastic robust chance-constrained programming (SRCCP) model for supporting MSW management. SRCCP combines advantages of the RO and CCP, and is effective in dealing with both model and solution robustness, and reflecting risks of constraints' violations. The compromise programming technique and the multi-objective simplex method will be used to solve the developed model. A solid waste management case will be presented to demonstrate the applicability of the proposed methodology.

2. Modeling formulation

2.1. Robust optimization

Robust optimization (RO) was firstly proposed by Mulvey et al. (1995). It is a method that can tackle the decision makers' favored risk aversion or service-level function, and yield a series of solutions that are progressively less sensitive to realizations of the data in a scenario set (Leung et al., 2007). The concept of "robust" herein has two main implications: solution robustness and model robustness. If the optimal solution provided by a robust-optimization model remains "close" to the optimal even if input data change, it is regarded as solution robustness. If solution is "almost" feasible for small changes in the input data, this is regarded as model robustness (Watkins and Mckinney, 1997). The model structure and definition of a RO model is different from that of a general optimization model. Two types of constraints are incorporated in a RO model: structural constraints and control constraints. Correspondingly, a RO model has two sets of variables, structural decision variables and control variables. The structural decision variables were similar with decision variable of the general model, and control variables were similar with uncertain variables, instead of the decision variables. The structural constraints are formulated following the concept of linear programming and their input data are free of any noise. Compared with the structural constraints, the control constraints are taken as an auxiliary constraints influenced by noisy data. The structural decision variables cannot be adjusted once a specific realization of the data has been observed, and the control variables are subjected to adjustment once the uncertain parameters are observed (Watkins and Mckinney, 1997; Leung et al., 2007). Let $x \in \{\Re\}^{n\times 1}$ be a vector of the structural decision variables, and $y \in \{\Re\}^{n\times 1}$ be a vector of control variables, where $\Re$ denotes a set of real numbers and n is the dimension. A robust-optimization model can be written as follows (Mulvey et al., 1995):

$$\text{Minimize } c^{\mathrm{T}}x + d^{\mathrm{T}}y \tag{1a}$$

Subject to:

$$Ax \le B \tag{1b}$$

$$Cx + Dy = E \tag{1c}$$

$$x, y \ge 0 \tag{1d}$$

where $c^{\mathrm{T}} \in \{\Re\}^{m\times n}$, $d^{\mathrm{T}} \in \{\Re\}^{m\times n}$, $A \in \{\Re\}^{m\times n}$, $B \in \{\Re\}^{m\times 1}$, $C \in \{\Re\}^{m\times n}$, $D \in \{\Re\}^{m\times n}$, $E \in \{\Re\}^{m\times 1}$; $\Re$ is a set of real numbers; m and n are dimensions. Eq. (1b) is the structural constraint whose coefficients are fixed and free of noise, while Eq. (1c) is the control constraint whose coefficients are subject to noise. Eq. (1d) ensures non-negative vectors.

In an OP model, the uncertain variables will present in the form of deterministic values under different scenarios, such as d, y, C,

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