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REVIEW

A review of inexact optimization modeling and its application to integrated water resources management

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Abstract Water is crucial in supporting people's daily life and the continual quest for socio-economic development. It is also a fundamental resource for ecosystems. Due to the associated complexities and uncertainties, as well as intensive competition over limited water resources between human beings and ecosystems, decision makers are facing increased pressure to respond effectively to various water-related issues and conflicts from an integrated point of view. This quandary requires a focused effort to resolve a wide range of issues related to water resources, as well as the associated economic and environmental implications. Effective systems analysis approaches under uncertainty that successfully address interactions, complexities, uncertainties, and changing conditions associated with water resources, human activities, and ecological conditions are desired, which requires a systematic investigation of the previous studies in relevant areas. Systems analysis and optimization modeling for integrated water resources management under uncertainty is thus comprehensively reviewed in this paper. A number of related methodologies and applications related to stochastic, fuzzy, and interval mathematical optimization modeling are examined. Then, their applications to integrated water resources management are presented. Perspectives of effective management schemes are investigated, demonstrating many demanding areas for enhanced research efforts, which include issues of data availability and reliability, concerns over uncertainty, necessity of post-modeling analysis, and the usefulness of the development of simulation techniques.

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1 Introduction

Water is crucial not only in supporting people's daily life and the continual quest for socio-economic development, but also for sustaining healthy ecosystems (Cai et al., 2009a; Tan et al., 2011a). Over several decades, the demand for fresh water in both sufficient quantities and satisfactory quality has been increasing steadily worldwide, along with population expansion, economic development, and living standard improvements, intensifying competition over limited water resources between human beings and ecosystems. At the same time, the depletion of source water, as well as public concerns over water-related environmental issues have greatly weakened society's capabilities in addressing potential risks and impacts associated with water supply. There is international consensus regarding the fact that water resources can no longer be consumed without addressing the issues of sustainability and the associated problems. Thus, planners and decision makers are facing increased pressure to respond effectively to many water-related issues and conflicts within multi-scale watersheds. This quandary requires a focused effort to resolve a wide range of issues, as well as the associated economic and environmental implications. Consequently, effective planning of water resources in an integrated manner (i.e., both quantity and quality for human beings and ecosystems) has been a priority for water managers and professionals, as well as regulatory agencies.

Nevertheless planning and management of water resources contains many processes such as forecasting water availability and demand, the evaluation and prediction of water contamination, as well as the resolution of water conflicts between human beings and ecosystems. This calls for the integrated management of water resources in terms of both water quantity and quality particularly between human beings and ecosystems. At the same time, many water related factors and processes are undergoing dramatic changes stemming from regulation implementation, regional/community development, and economic expansion, which collectively result in significant effects on water activities and the associated socio-economic and environmental implications. Also, the factors and processes are generally complicated with a number of economic, technical, environmental, legislative, and political factors. Moreover, such factors and their interactions are fraught with uncertainties that cannot be expressed as deterministic values or in an individual format (Huang et al., 2005a, b, c; Cai et al., 2009a, b, c; Tan et al., 2009, 2010a, b, c, d, 2011a, b, 2012). For example, within a specific watershed, randomness of specific natural events (such as precipitation) normally corresponds with many vague, subjective, and imprecise variables (such as economic factors), leading to multiple uncertainties. These uncertainties feature multiple dimensions and layers, and are thus complex by nature. Such dynamics and uncertainties may lead to a variety of complexities in water resources decision-making activities. The development of effective systems analysis approaches under uncertainty that successfully address the above interactions, complexities, uncertainties, and changing conditions is desired, which requires a systematic investigation of the previous studies on water systems.

Therefore, in this paper, a large number of systems analysis and advanced mathematical programming methods are presented in section 2, and modeling methods for integrated water resources management under uncertainty are discussed in section 3, followed by the conclusions and discussions.

2 Inexact modelling

Generally speaking, there are three types of uncertainties including intervals, possibilistic, and probabilistic distributions. Correspondingly, optimization modeling that is based on the three types of uncertainties can be categorized into stochastic, fuzzy, and interval mathematical programming.

2.1 Stochastic mathematical programming

Stochastic programming, as a mathematical (i.e., linear, nonlinear, integer, and mixed-integer) programming method, is based on probability theory. It requires that probability distributions of random parameters are known or can be estimated. Since the 1950s, the discipline of stochastic programming has grown to cover a wide range of models and solution approaches (Wets, 1996; Birge and Louveaux, 1997). One class of stochastic models applies to settings in which decisions are made repeatedly in essentially the same circumstances, and thus come up with a decision that will perform well on average (Shapiro and Philpott, 2010). Recourse programming, such as two- and multi-stage stochastic programs, generally fall into this category. Another class of stochastic programming models is averse to risk and seeks to safeguard the obtained solution against highly undesirable outcomes. Probabilistically constrained programming with individual or joint chance constraints can be considered as one of the classical modeling paradigms of this kind.

2.1.1 Recourse programming

A recourse decision refers to a decision that can be made in the second stage to compensate for any bad effects that might have been experienced as a result of the first-stage decision. The optimal policy from such a model is a single first-stage policy and a collection of recourse decisions (a decision rule) that define which second-stage action should be taken in response to each random outcome. In recourse problems, decisions are first made prior to the observation of random parameters, and further compensating decisions are allowed to be taken to minimize the expected consequences of the preciously taken decisions. The goal of recourse programming is to find some decision alternatives that are feasible for all (or almost all) of the possible parameter realizations, and to optimize the expectation of some functions of the decisions and the random variables (Birge and Louveaux, 1997; Kall and Meyer, 2005; Shapiro et al., 2009; Shapiro and Philpott, 2010). Two-stage stochastic programming with recourse was initially introduced by Beale (1955), and has been the most widely studied and applied stochastic programming method. In this method, there is an assumption that the probability distributions of parameters are independent from the decisions taken. The optimal policy from such a model is comprised of a single first-stage policy and a collection of recourse decisions (under a decision rule) defining the second-stage actions that should be taken in response to each random outcome (Shapiro and Philpott, 2010). In the first stage, decision makers take an action based on data available at the time that a decision has to be made. In the second stage, a recourse decision should be made to correct the first-stage decision that might have caused adverse effects due to the occurrence of a random event.

There exists a substantial body of literature regarding two-stage stochastic programming approaches and their applications in many areas (Edirisinghe and Ziemba, 1994; Schultz et al., 1996; Maqsood et al., 2004; Cai et al., 2009a–g). For example, Birge and Louveaux (1988) proposed a multicut algorithm for two-stage stochastic linear programs in order to reduce the number of major iterations in the solution process. Lustig et al. (1991) developed a two-stage stochastic programming and a solution algorithm based on a relevant interior point. Higle and Sen (1991) presented a cutting-plane algorithm for two-stage stochastic linear programming, which used randomly generated observations of random variables to construct statistical estimates of supports of the objective function. Edirisinghe and Ziemba (1994) developed a general approach for bounding the expectation of a saddle function through introducing limited moment information when random vectors had compact domains. Vladimirou and Zenios (1997) introduced the concept of restricted recourse which incorporated parameterized satisfying constraints in stochastic programming to enforce robustness in recourse decisions. Cheung and Chen (1998) formulated a two-stage stochastic network model that was solved using the stochastic linearization method and the stochastic hybrid approximation procedure. Beraldi et al. (2000) presented a specialized matrix factorization procedure for computing the dual step in a primal-dual path-following interior point algorithm to solve a two-stage stochastic linear programming model with restricted recourse decisions. Darby-Downman et al. (2002) proposed a two-stage stochastic programming model for determining optimal planting plans for a vegetable crop. In order to solve a linear two-stage stochastic programming problem with multiple quantile criterion, Kibzun and Nikulin (2001) proposed two algorithms based on the confidence approach and discrete approximation of the determined confidence set. Takriti and Ahmed (2004) incorporated robust optimization into the framework of two-stage planning systems to handle the variability of the second-stage costs. Albornoz et al. (2004) formulated a two-stage stochastic integer programming model with recourse for the planning of capacity expansion in a thermal system. Cho (2005) proposed a two-stage quadratic stochastic programming model that was solved through a log-barrier method. Bosch et al. (2007) extended the conventional two-stage linear stochastic program through imposing probabilistic constraints in the second-stage decision making process. Mehrotra and Ozevin (2007) introduced a two-stage stochastic semidefinite programming model and presented an interior point algorithm for solving this problem using Bender's decomposition. Tometzki and Engell (2009) proposed a stage decomposition-based hybrid evolutionary algorithm for two-stage stochastic integer programming problems, which employed an evolutionary algorithm to determine the here-and-now decisions and a standard mathematical programming method to optimize recourse decisions. Liu et al. (2009) modeled a network retrofit problem based on a two-stage stochastic programming model that could optimize a mean-risk objective of the system loss. An algorithm was also developed via extending the L-shaped method with generalized bender decomposition. Penuel et al. (2010) developed an integer decomposition algorithm for solving a stochastic scenario-based facility location problem with the consideration of second-stage activation costs. Karuppiah et al. (2010) presented a heuristic approximation strategy in order to reduce the number of scenarios in two-stage stochastic programming. Trukhanov et al. (2010) presented an adaptive multicut algorithm in order to dynamically adjust the aggregation levels of the optimality cuts in a two-stage stochastic linear programming model. Ntaimo (2010) introduced disjunctive decomposition to two-stage mixed 0-1 stochastic integer programming models with random recourse.

Multi-stage stochastic programming extends two-stage programming to a multi-stage setting. It applies to problems in which decisions should be sequentially made at certain periods of time based on information available at each time period. Within a multi-stage problem, each stage consists of a decision followed by a set of observations of the uncertain parameters which are gradually revealed over time. The objective is to minimize the expected costs of the consequences of these taken decisions. Multi-stage stochastic programming is closely related to, but differs from decision analysis, optimization of discrete event simulations, stochastic control theory, Markov decision processes, and dynamic programming (Kall and Meyer, 2005; Shapiro et al., 2009). Louveaux (1980) presented a computational procedure for solving multi-stage stochastic programming which had a quadratic objective function and a number of linear inequality constraints. Ruszczyński (1993) proposed a parallel decomposition method for multi-stage stochastic linear programming problems. Hwang and Singh (1998) formulated a multi-stage model for planning production in a serial production system where the aggregate productive capacity at each stage was uncertain. Ahmed et al. (2003) formulated a multi-stage stochastic integer programming model for solving a multi-resource capacity expansion problem. Liu and Sun (2004) combined the infeasible interior point methods and novel decomposition techniques in order to improve the computability of multi-stage stochastic linear programming models. Kuhn et al. (2008) introduced bounding approximations to a multi-stage stochastic program with expected value constraints. Zanjani et al. (2010) proposed a multi-stage programming approach for production planning under conditions of uncertainty in the quality of raw materials and demands.

2.1.2 Probabilistic programming

Probabilistically constrained programs do not require that the decisions are feasible for every outcome of the random parameters; instead, they aim at ensuring that a set of constraints will hold with certain probability level(s)

(Loucks et al., 1981; Birge and Louveaux, 1997; Shapiro et al., 2009). There are two main types of probabilistically constrained programming, chance-constrained programming with individual chance constraints, and joint probabilistic programming with joint chance constraints.

Chance-constrained programming was initiated in Charnes et al. (1958), and has attracted significant attention over the past decades. For example, Fortin and McBean (1983) employed chance constraints in order to handle uncertainties in the transfer coefficients of a linear programming model for supporting acid-rain abatement. Rakes and Reeves (1985) provided an approach for identifying tolerance levels within a chance constrained programming framework. Ellis et al. (1985, 1986) and Ellis (1991) proposed a linear chance-constrained stochastic model for supporting decisions of acid rain abatement. Guldmann (1986) proposed a chance-constrained programming approach for investigating interactions between weather stochasticity and pollution source/receptor locations in an air quality management problem. Weintraub and Vera (1991) developed a convergent plane algorithm for solving a nonlinear chance-constrained problem with normally distributed parameters. Shih and Frey (1995) proposed a multiobjective chance-constrained optimization model in order to address a coal blending problem targeted at reducing sulphur dioxide emissions from coal-fired power plants. Medova (1998) formulated a chance-constrained stochastic programming model for supporting the formulation of an integrated service network and the management of traffic measurements. Sawyer and Lin (1998) proposed several mixed-integer chance-constrained models for ground-water remediation. Kumral (2003) applied chance-constrained programming based on a multiobjective simulated annealing algorithm in order to solve a mineral blending problem in an industrial production process. Gurgur and Luxhoj (2003) utilized chance-constrained programming to address capital rationing problems with asymmetrically distributed cash flows. Cao et al. (2009) put forward several chance constrained mixed-integer nonlinear programming models for dealing with short-term refinery scheduling problems under uncertain demands of distillation units. Almadizar et al. (2009) applied a chance-constrained programming model to a group shop scheduling problem. Reddy and Adarsh (2010) proposed a chance-constrained model in order to support the optimal design of irrigation channels, and solved the model through adopting two mega-heuristic search algorithms.

Unlike chance-constrained programming pertaining to individual chance constraints, joint probabilistic programming seeks to find a decision that ensures the entire set of constraints being satisfied at a certain probability level. Miller and Wagner (1965) initially considered joint probabilistic constraints for independent random variables in the model's right-hand side coefficients. Watanabe and Ellis (1994) proposed a joint chance-constrained programming model that could not only incorporate within-constraint covariance, but also admit dependence between constraints. Chen et al. (2010) proposed a novel technique built on a classical worst case bound in order to deal with joint chance constrained optimization problems, which was applicable even if the constraints were correlated.

In a summary, stochastic mathematical programming can mainly reflect and handle uncertain information that can be expressed as probability distributions, representing a completed description of a specific variable and/or event. These PDFs can be obtained through statistical sampling. However, major disadvantages of stochastic mathematical programming include (i) the difficulties in acquiring and establishing PDFs of relevant parameters, (ii) the increase of the computational requirements, and (iii) the inconvenience in result explanations.

2.2 Fuzzy mathematical programming

Fuzzy mathematical programming representing the imprecision in a decision-making situation is founded on fuzzy sets theory pioneered by Zadeh (1965). Fuzzy mathematical programming has attracted the attention of many researchers, with a large number of studies in this area being conducted. Two kinds of uncertainty, ambiguity and vagueness, can be treated in fuzzy mathematical programming. Corresponding to these two kinds of uncertainty, fuzzy mathematical programming can be classified into two major categories: i) fuzzy flexible programming which addresses vagueness in the objective functions and constraints, and ii) fuzzy possibilistic programming which deals with ambiguous coefficients in both objective functions and constraints. Through integrating fuzzy mathematical programming into many other mathematical programming frameworks, a variety of extensions were derived, such as fuzzy integer programming, fuzzy dynamic programming, fuzzy multiobjective programming, and fuzzy nonlinear programming (Sakawa and Yano, 1994; Stanciulescu et al., 2003; Akter and Simonovic, 2005; Ganji et al., 2008).

2.2.1 Fuzzy flexible programming

Fuzzy flexible programming which represents mathematical programming with vagueness can address decision problems with fuzzy goals and fuzzy constraints (Bellman and Zadeh, 1970; Tanaka et al., 1973; Zimmermann, 1985). In fuzzy flexible programming, the flexibility in the targeted objective function values and the elasticity of the model's constraints, which correspond to fuzzy goals and fuzzy constraints, respectively, are both expressed as fuzzy membership functions and incorporated into optimization models. The general rule of fuzzy flexible programming is to maximize the degree of overall satisfaction for the constraints and objective. Bellman and Zadeh (1970) initiated the concept of fuzzy decisions and provided illustrative examples involving multistage decision processes. Sobral et al. (1981) illustrated a fuzzy optimization model with compromising alternative solutions to environmental management based on the investigation of different interest groups' subjective perspectives. Werners (1987) introduced an interactive decision support system in order to aid in solving multiobjective programming models that were subject to flexible constraints. Huang et al. (1993) developed an inexact fuzzy linear programming method in order to address vagueness in both the target value of system cost and in right-hand-side resource-availability limits. Buckley and Feuring (2000) designed an evolutionary algorithm in order to solve a fully fuzzified linear programming model and presented two applications that demonstrated the usefulness of the proposed approach. Karsak and Kuzgunkaya (2002) presented a fuzzy multi-objective programming approach in order to handle the vague nature of future investments and the uncertainty of the production environment in a flexible manufacturing system. Sakawa and Kato (2002) proposed an interactive fuzzy satisfying method for multiobjective multidimensional 0-1 knapsack problems. Mula et al. (2006) presented three fuzzy models for addressing a material requirements planning problem with flexibility in the objective function, the market demand, and the available capacity of resources. Huo and Wei (2008) proposed a fuzzy multi-objective integer programming model in order to deal with the supplier selection and order allocation problems in a supply chain system. Safaei et al. (2008) proposed a fuzzy programming-based approach in order to solve an extended mixed-integer programming model for dynamic cell formation problems, in which the degree of satisfying the fuzzy objective under the given constraints was maximized. Li and Hu (2008) proposed an interactive satisfying method based on alternative tolerance for handling fuzzy multiobjective optimization problems. Razmi et al. (2009) formulated a fuzzy integer programming model with fuzzy objectives and product demand vagueness in order to address supplier selection issues. Arora and Gupta (2009) presented an interactive fuzzy goal programming approach for bilevel programming problems with the characteristics of dynamic programming.

2.2.2 Fuzzy possiblistic programming

Fuzzy possibilistic programming contains mathematical programming with ambiguity as well as those with both vagueness and ambiguity (Inuiguchi et al., 1990, 1994; Inuiguchi and Sakawa, 1998; Inuiguchi and Ramík, 2000). In fuzzy possibilistic programming, fuzzy parameters are introduced into mathematical programming frameworks that can then be used to formulate various intermediate models based on the detailed specifications and analyses of specific problems. The uncertain parameters are represented as fuzzy regions where they possibly lay and are regarded as possibilistic distributions (Zadeh, 1975). A major strategy of fuzzy possiblisitic programming is the defuzzification of ambiguous coefficients in an optimization model so as to convert the problem into a corresponding deterministic one (Inuiguchi and Ramík, 2000). Over past decades, fuzzy possibilistic programming methods and the corresponding solution algorithms have been explored by many researchers across the world. For example, Campos and Verdegay (1989) employed possibility and necessity grades in order to address a fuzzy linear programming problem with imprecise coefficients in both matrix and right-hand sides of the constraint set. Otto et al. (1993) used the vertex method in order to approximate α-cuts of fuzzy sets. Fortemps and Roubens (1996) presented an area compensation procedure for addressing both normalized and non-normal fuzzy numbers in fuzzy possiblisitic programming. Yao and Wu (2000) proposed a fuzzy possibilistic programming approach based on the decomposition principle and the signed distance. Chang et al. (1996) used signed a distance ranking method in order to defuzzify fuzzy multiobjective programming into deterministic linear programming. Jamison and Lodwick (2001) introduced a penalty method based on the concept of an expected midpoint of fuzzy numbers in order to handle fuzzy linear programming problems. Torabi and Hassini (2008) proposed a multi-objective possibilistic mixed integer programming model for supply chain master planning. This possibilistic model was converted into an auxiliary crisp multiobjective linear model and was then solved through a novel interactive fuzzy approach. Zhang and Rong (2010) proposed a fuzzy possibilistic model for supporting the optimal scheduling of fuel gas systems, which utilized the necessity measure and alpha-level method in order to deal with imprecise parameters expressed as triangular possibilistic distributions. As a typical fuzzy possibilistic programming method, robust programming based on the concept of fuzzy intervals under a series of α-cut levels was widely studied (Dubois and Prade, 1988; Mulvey et al., 1995; Dubois et al., 2001). Robust programming was considered to be effective in handling problems with ambiguous coefficients as well as vague information of decision makers' implicit knowledge (Leung, 1988; Luhandjula and Gupta, 1996; Inuiguchi and Sakawa, 1998). In a robust programming model, the uncertain decision space is delimited by specifying uncertainties through the dimensional enlargement of the original fuzzy constraints, leading to enhanced robustness of the optimization process. Robust programming allows both left- and right-hand sides in a model's constraints to be represented as possibilistic distributions. The main limitation of this method remains in its difficulties in tackling uncertain parameters in the objective function, leading to potential losses of valuable uncertain information.

In a summary, fuzzy mathematical programming can mainly reflect and handle uncertain information that can be expressed as possibilistic distributions. Such distributions may be established based on decision makers' personal judgments and/or descriptions. This method does not require high quality data inputs like probability density functions (PDFs), representing a high applicability to many real-world cases with low data quality. However, fuzzy mathematical programming has its own shortages, such as (i) the fuzzy inputs may simplify relevant parameters for the optimization modeling, and (ii) the difficulties in obtaining stable fuzzy parameters to reduce the subjectivity of personal judgment.

2.3 Interval mathematical programming

The applicability of stochastic or fuzzy mathematical programming is limited because it is usually difficult to specify a probability distribution or membership function in an uncertain environment. Interval analysis was thus initiated in Moore (1979) and Alefeld and Herzberger (1983) in order to address uncertain optimization problems in which the uncertain coefficients' lower and upper bounds were required to approximate uncertainties, but their probability distributions or membership functions were not necessarily known. Over past decades, a number of interval analysis methods have been proposed. For example, Jansson (1988) developed a self-validating method for solving linear programming problems with interval data. Urli and Nadeau (1992) proposed interactive approaches for solving multiobjective linear programming problems with interval coefficients, in which non-deterministic objective functions and constraints were transformed into deterministic counterparts and were then solved using goal programming and chance-constrained programming. Matloka (1992) investigated the generalization of inexact linear programming methods and provided a corresponding solution algorithm. Chanas and Kuchta (1996) utilized preference relations in order to handle interval coefficients in the objective function of a linear programming problem. Tong (1994) transformed interval linear programming into conventional linear programming by introducing maximum value range and minimum value range inequalities. Sugimoto et al. (1995) advanced a parallel relaxation method for handling quadratic programming models with interval constraints. Sengupta et al. (2001) introduced the concept of an acceptability index and converted inequality constraints involving interval coefficients to their satisfactory crisp equivalent forms. Chen and Wu (2004) presented an interval optimization method for the dynamic vibration response of structures with interval parameters, and applied it to a truss structure and a frame structure to demonstrate the applicability of the developed model. Jiang et al. (2008) studied a nonlinear interval number programming problem in which the objective functions and the constraints were both nonlinear and uncertain inequalities.

Huang et al. (1992) pioneered an interval linear programming approach based on a two-step interactive algorithm. Such an approach exhibits the following merits: i) it allowed uncertainties to be directly communicated into the optimization and solution processes, ii) it did not require distributional or membership information for model parameters since interval numbers were acceptable as uncertain inputs in both the objective function and constraints, and iii) it did not lead to complicated intermediate models, and thus had relatively low computational requirements (Huang et al., 1995a–d). Huang's work has been further explored by many researchers over the world, evolving into one of the most vigorous branches of interval mathematical programming. In recent years, a wide range of interval mathematical programming methods have been developed, such as interval linear programming, interval nonlinear programming, interval dynamic programming, interval mixed integer programming, and interval multiobjective programming.

For example, Chang and Wang (1995) proposed an interval nonlinear programming approach for planning coastal wastewater treatment and disposal systems. Huang et al. (1995c) proposed an inexact quadratic programming method through the introduction of interval numbers into a quadratic programming framework, which could handle uncertainties expressed as discrete intervals and nonlinearities in cost functions. Yeh (1996) proposed several inexact linear and quadratic programming models for planning water resource management systems. Huang et al. (1996a) proposed an interval-parameter hop-skip-jump approach and the related computation algorithm for supporting land use planning under a climate change scenario. Bass et al. (1997) presented an interval-parameter multiobjective programming model in order to investigate the climate change impacts and facilitate adaptation planning in a Canadian watershed. Chi (1997) proposed an interval-parameter mixed integer linear programming model for the planning of waste diversion in the city of Regina; the model could deal with uncertainties expressed as discrete intervals and could tackle the problems of capacity-expansion planning and waste-flow allocation. Chen and Huang (2001) proposed a derivative algorithm for solving interval quadratic programming problems, which could greatly reduce computational efforts and facilitate its application to large-scale practical problems. Cheng et al. (2003) coupled multi-criteria decision analysis with inexact mixed integer linear programming methods in order to facilitate waste management and the allocation of waste flows in a landfill site, such that the total system cost could be minimized. The model was then applied to solving a real-world case study in the city of Regina, Canada. Davila and Chang (2005) developed a grey integer programming method and applied it to environmental management in the city of San Antonio in which interval parameters and decision variables were used for supporting capacity planning for a recycling facility under uncertainty; a variety of uncertainties in waste generation, routing distance, and recycling participation were also considered in the study. Davila et al. (2005) proposed a grey integer programming-based game theory for the system optimization and cost-benefit analysis of two competing landfills in the Lower Rio Grande Valley. Huang et al. (2005a, b) proposed a grey evolutionary simulation-optimization method for planning environmental management under uncertainty, which combined evolutionary simulation-optimization and grey programming techniques within a general framework. Through the developed approach, multiple policy alternatives meeting the required system criteria could be effectively created. Wu et al. (2006) addressed an interval nonlinear programming problem with a nonlinear objective function and a series of linear constraints for addressing the effects of scale economies on system costs. Chang and Hernandez (2008) formulated an interval mixed integer programming model to generate optimal expansion schemes for the sanitary sewer system in a fast-growing city in the US/Mexico borderlands. Ko and Chang (2008) formulated an interval nonlinear mixed integer programming model in order to optimize the utilization of co-firing biomass and refuse-derived fuel and to reduce the emission level of sulfur dioxide in a power plant in the United States. Rosenberg and Lund (2009) employed an interval-parameter mixed integer linear programming method for supporting cost-effective water management in Amman.

In a summary, interval mathematical programming can effectively address uncertain information that can be expressed as interval numbers. However, major disadvantages of interval mathematical programming include (i) the over simplification of input parameters that are expressed as pure intervals, and (ii) the possibility of infeasible solutions due to the enlargement of input interval parameters.

2.4 Hybrid inexact mathematical programming

Hybrid inexact mathematical programming has been emerging in order to address decision problems that are so complicated that they may be subject to more than one type of uncertainty (i.e., fuzziness, randomness, and interval numbers) (Dong et al., 2013). Most of the hybrid inexact programming methods are based on the integration of fuzzy and stochastic approaches, dealing with modeling issues where randomness and fuzziness co-occur in a decision making framework (Dong et al., 2012; Wang et al., 2013; Dai et al., 2014). During the rapid development of IMP, interval fuzzy methods as hybrids of interval and fuzzy programming, and interval stochastic methods as hybrids of interval and stochastic programming have also been introduced.

In the areas of fuzzy stochastic programming, Luhandjula (1996) proposed a fuzzy stochastic linear programming approach in order to address problems with fuzzy random variables, in which the original programming was reduced to a stochastic one via semi-infinite optimization so that it could be solved using stochastic optimization techniques. Hulsurkar et al. (1997) applied fuzzy programming to multiobjective stochastic linear programming problems. Liu (1998) proposed a spectrum of minimax chance-constrained programming models for fuzzy decision systems in order to find the best of the worst possible returns, and provided a fuzzy simulation based genetic algorithm for solving such minimax models. Mohammed (2000) introduced a chance-constrained fuzzy goal programming model where right-hand side coefficients were random variables distributed according to a uniform distribution. Liu et al. (2003) proposed a hybrid fuzzy-stochastic robust programming method for supporting regional air quality management, which was an extension of the chance-constrained programming and fuzzy robust programming methods. Huang (2007) proposed two chance-constrained programming models for capital budgeting, in which the net present values were considered as fuzzy numbers. A fuzzy simulation-based genetic algorithm was used for solving the problems, and two numerical examples were provided in order to illustrate the effectiveness of the proposed methodologies. Liu and Dai (2007) presented a two-stage fuzzy random minimum risk programming approach based on the mean chance theory. Ben Abdelaziz and Masri (2009) proposed a solution strategy consisting of fuzzy and stochastic transformation steps in order to solve a multi-stage stochastic programming with fuzzy probability distributions. Xu et al. (2009a) proposed a fuzzy chance-constrained model in order to identify optimal multi-project and multi-item investment combinations in many investment-planning problems. Schweickardt and Miranda (2009) presented a two-stage planning and controlling model for power distribution, which was based on a multi-criteria method integrating fuzzy dynamic programming and analytic hierarchy processes. Wang et al. (2009) proposed a two-stage fuzzy zero-one integer programming model in order to deal with a value-at-risk-based facility location problem. Sakawa and Katagiri (2010) incorporated an interactive fuzzy programming approach within a framework of two-level chance-constrained linear programming. Based on two-stage stochastic mixed-integer and robust programming approaches, Kara and Onut (2010) formulated a two-stage stochastic revenue-maximization model in order to determine long-term strategies for paper recycling in a reverse supply network. Sun et al. (2010) presented a two-stage fuzzy programming model with minimum-risk criteria in order to handle fuzzy variables with known possibilistic distributions in material procurement planning problems.

In terms of interval fuzzy programming and interval stochastic programming, Huang et al. (1995a) introduced an interval fuzzy integer programming method and its application to regional solid waste management planning. Wu et al. (1997) proposed a hybrid interval-parameter fuzzy multiobjective programming method and applied it to the case of water pollution control in a Chinese watershed. The method incorporated interval programming and fuzzy programming techniques within a multiobjective optimization framework. Sae-Lim (1999) proposed an inexact fuzzy-stochastic mixed integer linear programming model for the planning of waste management in a Canadian city. Huang and Loucks (2000) developed an interval-parameter two-stage stochastic programming (ITSP) model for water resources management. Maqsood et al. (2005) proposed an interval-parameter two-stage optimization model for irrigation planning. Du et al. (2005) proposed a reliability-based optimization model using a sequential single-loop procedure and reliability analysis in order to deal with the uncertain variables characterized by the mixture of probability distributions and intervals. Li et al. (2006) utilized fuzzy-robust programming and two-stage stochastic programming methods in order to address a regional air quality management problem. Karmakar and Mujumdar (2007) addressed the pollutant-loading allocation problem in a river system through a two-phase interval fuzzy mathematical programming model. Guo et al. (2008) proposed an interval-parameter two-stage stochastic semi-infinite programming method for addressing municipal solid waste management issues. Liu et al. (2008) incorporated fuzzy possibilistic programming and joint probabilistic programming into a mixed-integer programming framework for the expansion planning of a power generation plant. Luo and Zhou (2009) proposed a multi-stage interval-stochastic programming model using the expected value of long-term hydroelectric profit as the objective function to support the planning of hydroelectric resources.

3 Modelling of integrated water resources under uncertainty

Integrated Water Resource Management (IWRM) has been developed in order to “promote the coordinated development and management of water, land and related resources in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems” (Lenton and Muller, 2009). The concept was formally shaped in 1992 (Snellen and Schrevel, 2004). In this process, many uncertainties exist. A large number of studies were conducted to support the modeling of water systems management under uncertainty (Bender and Simonovic, 2000; Carter et al., 2005; Castelletti et al., 2008; Tan et al., 2013). These studies were based on SMP, FMP, and IMP, as well as their hybrids (Abu-Taleb and Mareschal, 1995; Chen et al., 2006; Bao and Fang, 2007; Cai et al., 2007, 2009a–g, 2011). They could tackle a variety of uncertainties embedded within the problems of water resources management.

In the areas of water resources management, Takeuchi (1986) formulated a chance-constrained programming model for real-time reservoir operation using a drought duration curve. Słowiński (1986) proposed interactive fuzzy multiobjective linear programming for water supply planning. Chang et al. (1996) developed a grey fuzzy multiobjective linear programming method for the evaluation of sustainable land development strategies in the Tweng-Wen watershed of Taiwan, China. Wu et al. (1997) proposed an interactive inexact-fuzzy multiobjective programming model for water pollution control in the Lake Erhai basin, China. Bass et al. (1997) presented an inexact multiobjective programming method for the planning of climate change adaptation within a water resources management system. Takyi and Lence (1999) proposed a multiple-realization chance constrained method which included several scenarios of design conditions in an optimization model for supporting surface water quality management. Sukyirun (2004) developed a chance-constrained linear programming model in order to support the long-term planning of water quality management in a basin in eastern Thailand. Karmakar and Mujumdar (2007) formulated a two-phase interval fuzzy mathematical programming model for addressing a waste load allocation problem in a river system. Saadatpour and Afshar (2007) presented a fuzzy waste load allocation model in which cost function and the water quality standards or the goals of dischargers and pollution control agencies were expressed as appropriate linear and/or nonlinear and nondecreasing and/or nonincreasing membership functions. Lu et al. (2008) developed an inexact two-stage fuzzy-stochastic programming method for water resources management where fuzzy sets theory was introduced into the conventional two-stage stochastic programming framework in order to represent various punishment policies under different water availability conditions. Li and Huang (2009) proposed a fuzzy-stochastic-based violation analysis method for planning water resources management systems within a multi-stream, multi-reservoir, and multi-period context. Xu et al. (2009b) proposed an inexact two-stage stochastic robust programming model based on the integration of interval linear programming, stochastic robust optimization, and two-stage stochastic programming techniques for dealing with water resources management under uncertainty. Liu and Huang (2009) proposed a dual-interval two-stage restricted-recourse programming method for flood diversion planning. Kataria et al. (2010) used truncated normal distributions in order to model stochastic water pollution, and incorporated them into a least-cost chance-constrained programming model. Guo et al. (2010) developed an inexact fuzzy-chance-constrained two-stage mixed integer linear programming approach for flood-diversion planning. Sadegh et al. (2010) developed a new methodology based on crisp and fuzzy Shapley games for optimal allocation of inter-basin water resources. Teegavarapu (2010) discussed the issues related to impacts of climate change on water resources and the application of a soft-computing approach based on fuzzy sets theory for climate-sensitive management of hydrosystems. Aviso et al. (2010) proposed a bi-level fuzzy optimization model for optimizing the water exchange network of plants in an eco-industrial park.

4 Conclusions

A multitude of inexact programming methods have been developed for tackling a variety of uncertainties in a broad spectrum of management problems. This indicates that uncertainty analysis in modeling studies has been attracting increasing attention in both academic and industrial communities. There are three major types of inexact mathematical programming methods, including stochastic, fuzzy, and interval mathematical programming methods. These three types of programming approaches are pertinent to three types of uncertainties which can be expressed as probability distributions, fuzzy sets, and interval variables, respectively. A number of inexact programming methods which can be classified into the three categories, as well as their derivatives and hybrids, have been developed and successfully applied to many areas of water resources management.

Despite several decades of research efforts in mathematical programming under uncertainty, many challenging issues are still unsettled. Most of the previous research took only a single type of uncertainty into account. Although a number of hybrid studies were recently conducted in order to address problems where different types of uncertainties exist in one system but in different parameters, previous studies encountered difficulties in tackling multiple types of uncertainties concurrently existing within an individual parameter, and thus could not reflect their synergistic and interactive effects on system analysis. Moreover, existing methods could not provide sufficient trade-off information between system robustness and optimality desired by decision makers. Furthermore, although inexact programming has been employed to address many environmental planning and management issues, its application to the areas of water management and water pollution mitigation has been relatively narrow. Particularly, there was a scarcity of studies that focused on the optimal planning of human activities in various economic sectors for the mitigation of water pollution emissions in a highly uncertain environment. Additionally, limited research has been conducted on the application of inexact optimization modeling for resolving water conflicts between human beings and ecosystems. Therefore, innovative inexact programming methodologies that are capable of characterizing the synergistic effects of multiple formats of uncertainties need to be advanced and then widely applied, in order to contend with the complexities of many aspects of water resources and ecosystem management.

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