DEVELOPMENT OF INEXACT OPTIMIZATION METHODS FOR PLANNING ENVIRONMENTAL MANAGEMENT SYSTEMS UNDER MULTIPLE UNCERTAINTIES

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ABSTRACT

Environmental planning is becoming a key component in environmental management due to rapid socio-economic development and steadily increasing population. In real-world applications, uncertainties and complexities are frequently involved in environmental management systems, where decision makers need sound management approaches in order to allocate their limited resources to different competing end users. Thus, more innovative approaches are required to deal with multiple uncertainties. As well more in-depth information in regard to the individual and interactive effects among multiple input parameters on the system performance is needed.

In this research, a dual-interval two-stage mixed-integer inexact-chance-constrained linear programming (DITMIC) method was developed for the planning of flood-diversion management systems. DITMIC did not only reflect uncertainties expressed as intervals, dual intervals, interval-valued probability distributions but also incorporated pre-regulated diversion policies into its optimization process. Various policy scenarios were generated and they were associated with varied economic penalties if the promised targets were violated. Furthermore, DITMIC assisted in analyzing dynamic features of capacity-expansion schemes when it came to decision-making. Various flood-diversion patterns and capacity-expansion schemes were obtained under different risk levels. The reliability of satisfying the system constraints under uncertainty was also examined. This enabled decision makers to choose the most desired outcome relative to their preference and perception of future conditions. To better enable insights on the detailed effects from uncertain parameters as well as their interactions on the system objective, a factorial dual-interval programming (FDIP) method was developed for planning municipal waste

management systems. Through the integration of factorial analysis and dual-interval linear programming into a general framework, the FDIP method could handle uncertainties existing in the left- and right-hand sides of the objective function, as well as in the associated constraints. Moreover, it had the advantages of identifying influential parameters along with their joint effects on the system output. Impact factors as well as their interactive effects have been identified and analyzed for the lower and upper bounds of the system output, which could further provide valuable information on their effects on the system solutions when it came to decision-making.

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CHAPTER 1

INTRODUCTION

Environmental planning is becoming a key component in environmental management due to rapid socio-economic development and steadily increasing population. When planning environmental management systems, a number of interconnected components related to technical, socio-economic, environmental, institutional, political and financial aspects need to be taken into consideration since they result in amplified system complexities (Zarghaami, 2006). For example, in water resources management, conflicts are often associated with issues of water supply and demand, leading to major barriers to sustainable management of the water resources (Maqssod et al., 2005; Wang, 2010). However, in real-world environmental management systems, a number of their components are often associated with uncertainties. These uncertainties and the related complexities are further intensified due to the existence of various interactive relationships, leading to difficulties in providing practical and efficient management plans, as well as discovering individual and interactive effects among a number of impact factors. Therefore, innovative optimization methodologies that can tackle such complex uncertainties are needed.

During the past decades, Interval Mathematical Programming (IMP), Stochastic Mathematical Programming (SMP), and Fuzzy Mathematical Programming (FMP) have been widely adopted as supports for the planning of environmental management systems under uncertainty (Huang, 1994). Among them, IMP allows uncertainties to be expressed as intervals, instead of probabilistic distributions or possibility distributions, due to the fact that the available information is often incomplete and/or imprecise. The intervals are with known lower bound and upper bound (e.g., lower bound and upper bound of a parameter are deterministic). Moreover, IMP improves upon conventional optimization methods regarding its solution algorithm and computation requirement. For instance, the generated interval solutions from the IMP method can reflect uncertainties that are embedded in the concerned systems, and they are convenient for managers to interpret and adjust the decision schemes according to practical situations (Cao and Huang, 2011; Cao et al., 2011). In fact, a great number of optimization techniques related to IMP were developed during the past decades (Huang et al., 1992; Huang, 1996; Maqsood and Huang, 2003; Maqsood et al., 2005; Li et al., 2006; Lin and Huang, 2008; Qin et al., 2009; Cao et al., 2011). However, IMP might become incapable of dealing with the parameters that are associated with the following characteristics. Firstly, system parameters are highly uncertain. Secondly, system parameters exist in the model's right-hand-side. Moreover, IMP method lacks the ability to reflect and examine economic consequences of violating the policies.

Unlike the IMP method, the SMP method has the ability to allow probabilistic information to be directly incorporated into the optimization framework, and it is effective in dealing with uncertainties that exist in the model's right-hand-side. There are two major categories of SMP. The first is the chance-constrained programming method, abbreviated as CCP; the second is the two-stage stochastic programming method, abbreviated as TSP. In general, CCP is effective in tackling uncertainties expressed as probability distributions on the model's right-hand-side and it can also reflect the reliability of satisfying (or risk of violating) the system constraints under uncertainty (Loucks et al., 1981; Huang, 1998; Li et al., 2007b). CCP has been applied to a diverse range of environmental management problems containing system complexities and uncertainties (Ellis et al., 1985, 1986; Huang, 1998; Huang et al., 2001; Li et al., 2007b; Qin et al., 2009; Tan et al., 2011; Xie et al., 2011; Dai et al., 2012; Sun et al., 2013). However, it has difficulties in handling independent uncertain parameters in the constraint's left-hand-side, as well as the cost coefficients in the objective function (Roubens and Teghem, 1991; Huang, 1998). Furthermore, CCP is unable to deal with various policy scenarios that are associated with different levels of economic penalties when the promised targets are violated (Li et al., 2007a).

TSP is effective in examining policy scenarios when the system parameters are characterized by uncertainty (Maqsood and Huang, 2003). The fundamental idea behind TSP is the ability to take corrective action after random events have occurred, and this concept is often known as *recourse*. In TSP, a decision (first-stage decision) is initially carried out prior to the occurrence of the random events. After the random events have taken place and their values are known, a second decision (second-stage decision) can be undertaken in order to minimize "penalties" (Loucks et al., 1981; Birge and Louveaux, 1988). Additionally, TSP can be effective in tackling uncertainties expressed as probability density functions (PDFs) and it can also account for economic penalties with recourse against any infeasibility (Maqsood et al., 2005; Fan et al., 2012). Numerous studies have been conducted through implementing the TSP method (Mobasheri and Harboe, 1970; Bard, 1983; Pereira and Pinto, 1991; Ferrero et al., 1998; Huang and Loucks, 2000; Uribe et al., 2003; Sayın and Kouvelis, 2005; Beraldi et al., 2008; Marufuzzaman et al., 2014). However, it might be challenging to adopt the TSP method in order to reflect uncertainties in large-scaled optimization models (Huang and Loucks, 2000).

The above methods are often integrated in order to deal with system complexities that are associated with dual or multiple uncertainties in environmental management systems (Maqsood et al., 2005; Luo et al., 2006; Guo et al., 2008; Qin and Huang, 2009; Xu et al., 2009; Lin and Huang, 2010; Xie et al., 2011; Dong et al., 2012, 2013; Sun et al., 2013; Ji et al., 2014). Even if such integrations are effective in handling uncertainties expressed in multiple forms that co-exist in environmental management systems, it still lacks the ability to effectively handle those that are highly inaccurate; thus, conventional optimization techniques may no longer be efficient in tackling such problems. Actually, in real-world applications, uncertainties in the system components may be presented in various formats, leading to dual or multiple uncertainties. Moreover, when the uncertain parameters cannot be expressed as probability distribution functions, the concept of dual-interval may become more attractive (Liu et al., 2009). In general, dual interval refers to a situation where the boundaries of an interval-valued number are presented as interval numbers. For example, $[a, b]$ is an interval whose boundaries are associated with deterministic values, e.g., a and b. In comparison, $\left[[a, c], [d, b]\right]$ is dual interval, where $[a, c]$ and $[d, b]$ are the uncertain lower bound and upper bound of the dual interval. Generally, the adoption of dual interval is on the following premises. Firstly, insufficient information is presented during the process of information acquisition; secondly, the number of samples is too small to construct probability distribution functions (Liu and Huang, 2009; Liu et al., 2009).

In addition, previous efforts were proposed through adopting various optimization techniques as well as their integrations. However, such efforts could hardly reflect the embedded effects of an individual parameter as well as their interactive effects. In other words, even if conventional optimization techniques had the ability of providing sound decision support, it could hardly point out why it should be done in a certain way and which part of the system components and/or the associated parameters were affecting it. If this could be discovered, such components usefulness would receive much attention. Therefore, more innovative techniques are needed to analyze the influences of individual parameters and their joint-effects on the targeted system performance.

Factorial analysis is a technique which has been extensively applied to a range of disciplines, such as industry, psychology, education, agriculture, medical treatment and engineering (Loh et al., 1989; Vicente et al., 1998; Burkert et al., 2004; Dillen et al., 2004; Rekow et al., 2006; Qin et al., 2008; Onsekizoglu et al., 2010; Chowdhury et al., 2011; Zhou and Huang, 2011; Fontana, 2013; Fontana and Sampo, 2013; Fu et al., 2013; Wang and Huang, 2014). The fundamental idea behind factorial analysis is to arrange modeling responses in such a way that the variation in the modeling responses is obtained under different combinations of the input parameters (Box et al., 1978; Qin et al., 2008; Zhou and Huang, 2011). Factorial analysis can not only quantitatively analyze the effect of individual input parameters on the system output, but also reflect joint-effects among multiple modeling parameters on the system performance at the same time. As a result, factorial analysis can be introduced into the optimization framework in order to properly address the problems and provide more insightful information regarding decision-making when planning of environmental management systems.

Therefore, this research aims to develop two optimization methods for supporting resources and environmental management under dual or multiple uncertainties. In detail, a dual-interval two-stage mixed-integer inexact-chance-constrained linear programming (DITMIC) method is proposed for planning flood-diversion management systems under multiple uncertainties; furthermore, a factorial dual-interval programming (FDIP) method will be developed for planning municipal waste management systems.

This dissertation is divided into five chapters. Chapter 1 gives a general introduction on current issues associated with the planning of environmental management systems; the objectives of this research are also defined in this chapter. Chapter 2 presents a literature review regarding previous studies of optimization techniques used in planning environmental management systems. Chapter 3 introduces the development of a dual-interval two-stage mixed-integer inexact-chance-constrained linear programming (DITMIC) method for planning flood-diversion management systems under multiple uncertainties. Chapter 4 shows the development of a factorial dual-interval programming (FDIP) method for planning municipal waste management systems. Chapter 5 gives brief conclusions for this dissertation.

CHAPTER 2

LITERATURE REVIEW

2.1 Deterministic optimization modeling for the planning of environmental management systems

Deterministic optimization techniques, such as linear programming, nonlinear programming, mixed integer programming, and dynamic programming, have been widely applied to assist the planning of environmental management systems. In the case of municipal solid waste management systems, deterministic optimization methods were adopted since the 1970's (Morrissey and Browne, 2004). For example, Esmaili (1972) presented a dynamic optimization model on the selection of the combination of processing or disposal facilities, or both, from a number of alternative facilities. The proposed model was to minimize the overall cost of solid waste management operations with regard to hauling, processing or disposal, or both. Fuertes et al. (1974) proposed location models for regional solid waste management facilities within a linear programming framework. The methodology took into consideration the trade-offs between system cost and various equity issues such as esthetics, size and number of regional facilities. Peirce and Davidson (1982) identified a cost effective configuration of transportation routes, transfer stations, processing facilities, and secure long-term storage impoundments by investigating the relative costs of regional and state-wide hazardous waste management schemes through linear programming. Baetz et al. (1990) adopted dynamic programming to determine the optimal sizing and timing for landfills and waste-to-energy facilities. Chang and Wang (1996) applied a multi-objective mixed-integer programming method to handle the potential conflict between environment and economic goals as well as to evaluate sustainable strategies for waste management in the city of Kaohsiung in Taiwan. In this method, economic impacts, air quality impacts, noise impacts, and traffic flow increments were incorporated into the optimization objectives. The associated constraints included mass balance, capacity limitation, operation, financial and related environmental quality constraints. Optimal strategies were obtained from such a method and they could provide various total solutions for evaluation of long-term waste stream allocation, siting, resource recovery and tipping fees. Everett and Modak (1996) presented a deterministic linear programming model to help decision makers in the long-term scheduling of disposal and diversion options in a regional integrated solid waste management system. In this model, the objective was to minimize the cost over a lengthy planning period by answering questions such as what types of integrated solid waste management programs to implement, and when to implement them. The model was able to deal with multiple communities, landfills, and incinerators; it could also incorporate mutually exclusive collection and facility options. Costi et al. (2004) developed a decision support system (DSS) to help decision makers in the planning of municipal solid waste management. Such a DSS was based on a nonlinear optimization problem containing binary and continuous variables. The objective involved all possible economic costs and the constraints included technical, normative, and environmental issues. Badran and El-Haggar (2006) developed a mixed-integer programming model for a municipal solid waste management system in Port Said, Egypt. The concept of collection stations was incorporated into the model and the municipal solid waste management system cost was to be minimized. Minciardi et al. (2008) presented a nonlinear, multi-objective programming method to support the decision-making on the optimal flows of solid waste sent to landfills, recycling, and different types of treatment plants. In this method, four objectives related to economic costs, un-recycled waste, sanitary landfill disposal and incinerator emissions were to be minimized.

In the case of deterministic optimization approaches for water resources management, Kim and Mays (1994) presented a mixed-integer nonlinear programming method for the rehabilitation and/or replacement in an existing water-distribution system. Mckinney and Lin (1995) adopted a mixed-integer nonlinear programming model in order to find the minimum cost design of an aquifer remediation system. Randall et al. (1997) presented a mixed-integer linear programming method for water supply operations, which has been applied by the Alameda County Water District (California) for its long-range and integrated planning. Nishikawa (1998) developed a simulation-optimization model for the management of water resources during a drought in the city of Santa Barbara. Ground-water simulation and linear programming were linked together within such a model. The objective was to minimize the cost of water supply under the related constraints of water demand, hydraulic head and water capacity. Srinivasan et al. (1999) provided a mixed-integer programming model for the planning of water-supply reservoir performance optimization, which contained performance indicators such as reliability, resilience, and vulnerability. Tu et al. (2003) developed a mixed-integer linear programming model and applied it to a multi-reservoir system in the southern region of Taiwan. The proposed model considered both the traditional reservoir rule curves and the hedging rules in order to provide guidelines for reservoir releases.

However, in many real-world applications associated with the planning of environmental management systems, uncertain information exists in many system components, resulting in a more complex situation. Thus, deterministic optimization techniques can no longer be efficient since they cannot provide decision alternatives nor can they gain insights into the performance of such environmental management systems. Therefore, more advanced optimization methodologies which consider the complexities and uncertainties in the planning of environmental management systems are desired.

2.2 Optimization modeling on the planning of environmental management systems under uncertainty

2.2.1 Two-stage stochastic programming

Two-stage stochastic programming (TSP) is one of the major types of Stochastic Mathematical Programming (SMP). It is effective for solving management problems where decisions need to be made periodically and the associated data are mostly uncertain (Huang and Loucks, 2000). The fundamental idea behind TSP is the concept of recourse in which a decision is firstly undertaken before values of the random variables are known. In turn, after the random events have happened and their values are known, a second decision is made in order to take corrective actions (e.g., minimizing "penalties" that may appear due to any infeasibility) following these random events (Loucks et al., 1981; Birge and Louveaux, 1988; Ruszczynski, 1993; Huang and Loucks, 2000; Huang et al., 2007; Guo and Huang, 2009). In TSP, the initial decision is called the first-stage decision and the corrective action is called the second-stage decision (Huang and Loucks, 2000).

Algorithms of TSP were widely explored and investigated since the 1960's, and their applications on the planning of environmental management systems have been reported (Wets, 1974; Kall, 1979; Loucks et al., 1981; Birge and Louveaux, 1988; Higle and Sen, 1991; Damsleth et al., 1992; Cheung and Chen, 1998; Darby-Dowman et al., 2000; Kibzun and Nikulin, 2001; Albornoz et al., 2004; Leung and Wu, 2005; Borghetti et al., 2007; Beraldi et al., 2008). For example, Mobasheri and Harboe (1970) developed a two-stage optimization method to determine the optimum design and operation of a single multipurpose reservoir. Lund and Israel (1995) presented two-stage and multistage linear programming methods to estimate the least-cost integration of several water marketing opportunities, including dry-year options and spot-market water transfers. Ferrero et al. (1998) developed a dynamic two-stage programming method for long-term hydrothermal scheduling of multi-reservoir systems. Albornoz et al. (2004) presented a two-stage stochastic integer programming method to obtain the optimum policy in the capacity expansion planning of a particular thermal-electric power system. Lee et al. (2006) developed a two-stage stochastic model to deal with the uncertainties that exist in reservoir operation planning due to inflow uncertainty relative to determine the efficient monthly target reservoir storage. Han and Lee (2011) developed a two-stage stochastic programming model for the planning of carbon capture and storage infrastructures for CO_2 utilization and disposal under stochastic CO_2 emissions.

2.2.2 Chance-constrained programming

Chance-constrained programming (CCP) is another type of Stochastic Mathematical Programming (SMP) developed by (Charnes and Cooper, 1959). Charnes and Cooper (1959). It is regarded as a powerful method in reflecting risk violation or reliability of satisfying system constraints under uncertainty. In the CCP method, it is usually unnecessary for the system constraints to be totally satisfied at all time. Instead, they can be satisfied in a proportion of cases with given probabilities (Loucks et al., 1981; Li, 2007). The CCP method is effective in dealing with uncertainties at the right-hand-side of the constraints when their probability distributions are available (Morgan et al., 1993; Li, 2007). A number of studies have been conducted in relation to the development of enhanced CCP approaches which are widely applied to the planning of environmental management problems (Revelle et al., 1969; Askew, 1974; Houck et al., 1980; Ellis et al., 1985, 1986; Tung, 1986; Strycharczyk and Stedinger, 1987; Fujiwara et al., 1988; Dupacova et al., 1991; Morgan et al., 1993; Kataria et al., 2010; Ji et al., 2014). For example, Lohani and Thanh (1978) developed a chance-constrained programming model with the objective of minimizing the total operating cost of biochemical oxygen demand (BOD) removal by determining the degree of removal required at each treatment facility without violating the desired dissolved oxygen (DO) standards in the stream. Later on, Lohani and Saleemi (1982) extended the chance-constrained technique to include wastewater flow, de-oxygenation rate, re-aeration rate, and water strength as random variables. In addition, Guldmann (1986) investigated the interactions between weather stochasticity and the locations of pollution sources and receptors in air quality planning. The formulated chance-constrained approach was to account for the inter-annual randomness of the metrological conditions and for the locations of pollution sources and receptors.

Moreover, Dupacova et al. (1991) developed a chance-constrained model for water management of a real-life water resources system in Eastern Czechoslovakia. Shih and Frey (1995) developed a multi-objective chance-constrained optimization model for reducing sulfur emissions from coal-fired power plants. The expected costs were to be minimized and chance constraints were related to risk measures such as the standard deviation of coal blending costs, the expected sulfur emissions and the standard deviation in sulfur emissions. Edirisinghe et al. (2000) proposed a mathematical programming model for the capacity planning for a multipurpose water reservoir. The model was based on the CCP method recognizing the randomness in stream flow and incorporated a special target-priority policy according to given system reliabilities.

More recently, Yang and Wen (2005) proposed a new chance-constrained programming method for the planning of an optimal transmission system expansion with several uncertain factors such as the locations and capacities of new power plants and future load demands. These were modeled as specified probability distributions. An and Eheart (2007) presented a screening technique for using chance-constrained programming to achieve an overall system (e.g., joint) reliability. The method was illustrated for airborne particulate emissions control, in which the overall cost of controlling particulate emissions from two electrostatic precipitators was minimized in a manner that maintains ground-level particulate concentration, at all receptors with a prescribed reliability. Mesfin and Shuhaimi (2010) proposed a chance-constrained model for a gas processing plant under uncertain feed flow rate and composition. Zhang and Li (2011) introduced the chance-constrained programming approach to optimal power flow (OPF) under uncertainty. Hajian et al. (2012) proposed a chance-constrained optimization (CCO) method to handle uncertainty in control of transmission voltages.

2.2.3 Two-stage stochastic integer programming

Two-stage integer programming (TSIP) methods were widely investigated and improved during the past decades. Its associated applications range from allocation selection to resources allocation and capacity expansion under stochastic uncertainty

(Wollmer, 1980; Eppen et al., 1989; Fine and Freund, 1990; Berman et al., 1994; Schultz et al., 1996; Caroe and Tind, 1998; Klein-Haneveld and van der Vlerk, 1999; Schultz, 2003; Ahmed et al., 2004; Sen and Sherali, 2006). For example, Nurnberg and Romisch (2002) proposed a two-stage stochastic programming model for the planning of short- or mid-term cost-optimal electric power production. Uncertainties were related to the demand (or load) and prices for fuel, as well as for the delivery contracts of the generated power. The model considered a large number of mixed-integer (stochastic) decision variables and constraints linking time periods and operating power units. Albornoz et al. (2004) presented a two-stage stochastic integer programming method for obtaining of an optimum policy in the capacity expansion planning of a particular thermal-electric power system. The uncertainties were related to future availability of the thermal plants currently under operation and were reflected through a finite group of scenarios. Rico-Ramirez et al. (2007) developed a two-stage mixed-integer stochastic programming method for the optimal placement of sensors in municipal water networks to detect maliciously injected contaminants. The model includes uncertainties in the attack risk and population density, with a minimized expected fraction of the population at risk and the cost of the sensors. In this model, the locations of a number of sensors were the first stage decision variables, whereas the second stage evaluated the population at risk for the scenario obtained in the first stage. The information was then used to modify the first stage decisions for the next iteration. Beraldi et al. (2008) proposed a two-stage stochastic integer programming model for the integrated optimization of power production and trading which include a specific measure accounting for risk management.

2.2.4 Interval mathematical programming

In 1966, Moore (1966) firstly introduced the theory of interval analysis. Later on, Interval Mathematical Programming (IMP) was developed as a branch of interval analysis theory (Huang et al., 1992). The IMP is useful in dealing with uncertainties that exist in a system analysis, in which the uncertain input parameters are expressed as intervals with known lower bound and upper bound but unknown distribution functions (Huang et al., 1992). The IMP is more advantageous compared to the conventional methods due to its various characteristics. Firstly, the IMP method has the ability to allow uncertain parameters to be directly incorporated into the model and communicated into the optimization processes. Therefore, solutions reflecting the inherent uncertainties can be generated. Secondly, the IMP method does not lead to more complicated intermediate model. As a result, its low computational requirements allow it to be easily applied to practical problems. Thirdly, the IMP method does not require distributional information since interval numbers were already acceptable as uncertain input parameters. This is particularly meaningful for practical applications as it is usually much more difficult for planners to specify probability distributions than to define only fluctuation intervals (Huang et al., 1992; Huang and Moore, 1993; Huang et al., 1995).

During the past several decades, extensive literature has been cited on the applications of interval linear programming in mathematical optimization problems. Some were widely applied to the planning of environmental management systems. For example, Ishibuchi and Tanaka (1990) investigated the IMP problem through converting the objective function into a multi-objective problem (e.g., maximization and minimization problem) using order relations. Matloka (1992) studied the generalization of the Inexact Linear Programming (ILP) method and provided relevant solution algorithms accordingly. Huang (1996) provided an interval parameter water quality management (IPWM) model and applied it to a case study of water pollution control planning within an agricultural system. Moreover, Huang et al. (1992, 1995, 1997, 1998) and Huang (1994, 1996) developed a series of interval mathematical programming methods to deal with system uncertainties. These methods have been applied to a number of problems related to the planning of environmental management systems ranging from solid waste management, water resources management, and air pollution control planning to energy systems optimization.

Furthermore, the developed inexact mathematical methods were adopted into some real-world case studies which are usually related to resources and environmental planning problems. For example, Li and Huang (2006) developed an interval-parameter two-stage mixed-integer linear programming (ITMILP) model and applied it to the long-term planning of waste management activities in the City of Regina, Saskatchewan, Canada. Lin et al. (2010) proposed an interval-energy system model for supporting regional energy systems planning under uncertainty. Dong et al. (2012) developed an inexact optimization modeling approach (IBEM: inexact Beijing energy model) for supporting energy systems planning and air pollution mitigation under uncertainty.

In summary, one common characteristic of the abovementioned optimization methodologies is that they have the ability to deal with system analysis involving single uncertainty (e.g., intervals or probability distributions). However, such methodologies become deficient when dual or multiple uncertainties expressed in various forms exist in the system components. As a result, integrated optimization methodologies for the planning of environmental management systems were developed with consideration of dual or multiple uncertainties.

2.3 Optimization modeling on the planning of environmental management systems under dual or multiple uncertainties

In real-world applications, environmental management systems include various interconnected components which exhibit significantly more complexity than their individual parts. In order to tackle these uncertainties, a number of optimization techniques related to dual- or multiple uncertainties were proposed. For example, Nie et al. (2008) developed an inexact fuzzy water management model for water quality management within an agricultural system. Cheng et al. (2009) introduced an integrated chance-constrained programming and interval-parameter linear programming approach, known as the random-boundary-interval linear programming (RBILP) method, in which intervals with uncertain lower bound and upper bound were handled through introducing the concept of random boundary interval. The proposed method was applied to the planning of municipal solid waste (MSW) management under dual uncertainties. Wang and Huang (2013b) proposed an interactive fuzzy boundary interval programming (IFBIP) approach for tackling dual uncertainties that exist in the objective function and the left- and right-hand sides of the constraints. The approach was applied to a regional air quality management problem. Additionally, Zhou et al. (2013b) proposed an interval-stochastic fractile optimization (ISFO) model for developing optimal water-resources management strategies for the Kaidu-kongque watershed under multiple uncertainties. The ISFO model can handle uncertainties presented as probability distributions and intervals with possibility distribution boundaries.

However, limitations occur when distributional information on the boundaries of the uncertain parameters is not readily available and the collected information on the input modeling variable are insufficient to construct possibility and/or probability distributions of the boundaries (Liu et al., 2009). In fact, the boundaries of the intervals will become more imprecise due to highly uncertain information resulting from either situations such as the fluctuation of daily capacity of a Waste-to-Energy (WTE) facility (Cai et al., 2007). or given by the decision makers regarding their different implicit knowledge on certain aspects of the systems, in turn, leading to the presence of dual uncertainties. The major shortcoming of the above techniques is that relative solutions might not be successfully obtained when there is lack of information.

2.3.1 Dual-interval linear programming

In order to deal with such problems, a new concept of dual interval was introduced to the optimization process (Liu et al., 2009). Unlike single interval, such as $[a, b]$, with deterministic boundaries a and b, a dual interval $\left[[a, c], [d, b]\right]$ carries interval bounds $[a, c]$ and $[d, b]$, which represent the uncertainties in the lower bound and upper bound of a single interval. Dual interval can not only cover the problem where enough information is presented, but also handle a situation where highly uncertain (or low quality) information is available (Liu et al., 2009).

Previously, a number of studies were reported on dealing with dual-interval linear programming within an optimization framework. Practical applications to specific problems regarding environmental management systems were also analyzed. For example, Liu et al. (2009) developed a dual-interval parameter linear programming (DILP) model in which the lower and upper boundaries of several interval-valued parameters were expressed as intervals. The model was applied to the long-term planning of municipal solid waste (MSW) management systems under uncertainty. During the same year, Liu and Huang (2009) presented a dual interval two-stage restricted-recourse programming (DITRP) method for flood-diversion planning under uncertainty. Moreover, Li et al. (2010a) developed a dual-interval vertex analysis (DIVA) method through incorporating the vertex method within an interval-parameter programming framework and applied it to a regional air pollution control problem. In the DIVA method, uncertain parameters were presented as dual intervals that exist in the objective function and both the left-hand-side and right-hand-side of the modelling constraints. Jin et al. (2012) developed a dynamic dual interval programming (DDIP) method and applied it to an irrigation water allocation system with uncertainty.

2.4 Factorial analysis

Factorial analysis can be regarded as a practical tool in experimental design. In particular, the associated techniques are regarded as a critically effective means in the engineering world for improving the performance of manufacturing processes, as well as in the development of new processes (Zhou and Huang, 2011).

In fact, factorial analysis has been applied with broad applications in various disciplines, such as agricultural, psychological, educational, medical and/or clinical, chemical engineering, and industrial engineering fields (Baxter, 1940; Holland and Cravens, 1973; Stampfer et al., 1985; Wehrle et al., 1995; Dillen et al., 2004; Ahluwalia et al., 2006; Ponnusami et al., 2007; Kehoe et al., 2011; Meski et al., 2011; Safa and Bhatti, 2011a, 2011b; Camacho et al., 2013; Ding et al., 2013; Stojanović, 2013). For example, Fannin et al. (1981) performed a fractional factorial design to investigate main and interactive effects of environmental factors on phenol biodegradation in a shake-flask system, where the number of experiments necessary to evaluate multi-factor interactions was greatly reduced. Loh et al. (1989) conducted a 3^4 factorial design on a vertical machining centre to establish the effects of ball-burnishing parameters on the surface roughness of AISI 1045 specimens. Vicente et al. (1998) carried out work on the screening process of different types of catalysts for the transesterification reaction of sunflower oil (SFO) with methanol, in which the experimental factorial design and response surface methodology were applied in order to determine the optimum values for the variables affecting the process. In addition, Burkert et al. (2004) adopted factorial design along with response surface analysis to study the effect of carbon source (soy oil, olive oil and glucose) and nitrogen source concentrations (corn steep liquor and NH_4NO_3) on the lipase production by *Geotrichum* sp. at 30 degrees Celsius and the optimal conditions for lipase production. In this research, a total of five factorial designs were carried out: a 2^4 factorial design was performed to study the effects of glucose concentration (CSL) and ammonium nitrate concentration (NH_4NO_3) with 1% olive oil (OO) or soy oil (SO); two 2^3 factorial designs were employed to study the concentrations of CSL, ammonium nitrate and soy oil; and two other 2^3 factorial designs were carried out to study the effects of CSL, ammonium nitrate and olive oil. Moreover, Onsekizoglu et al. (2010) used a two-level factorial experimental design to investigate the influence of the main operating parameters on evaporation flux and soluble solid content of apple juice during concentration through osmotic distillation (OD) and membrane distillation (MD) processes. Chowdhury et al. (2011) carried out a factorial design at two levels and four factors to investigate the potential for hydrogen generation using Y-sensitized

TiO_2/Pt catalyst under visible solar light in the presence of triethanolamine (TEOA) as an electron donor. Jaynes et al. (2013) reported a new application of the fractional factorial design to investigate a biological system with HSV-1 and six antiviral drugs. Sequential use of two-level and three-level fractional factorial designs were adopted to screen important drug and drug interactions, as well as to determine potential optimal drug dosages through the use of contour plots.

More recently, factorial analysis has been frequently adopted into the simulation and optimization processes within environmental management systems planning under uncertainty. Its main task was to reveal the influences of various uncertain inputs and their joint-effects on the system performance. For example, Qin et al. (2008) developed a factorial-design-based stochastic modelling system (FSMS) to systematically investigate impacts of four uncertain parameters associated with subsurface hydrocarbon-contaminant transport. The results revealed that the uncertainties in input parameters pose considerable influence on the predicted output and can provide useful information for further decision-making regarding the petroleum contamination problem. Zhou and Huang (2011) proposed a factorial two-stage stochastic programming (FTSP) approach for water resources management under uncertainty. In this study, a 2^{9-3} fractional factorial design was conducted in order to identify the individual and combined effects of 9 uncertain parameters on the net system benefit. Zhou et al. (2013a) later expanded the method and proposed a factorial multi-stage stochastic programming (FMSP) approach to support water resources management under uncertainty. The results provided desired water-allocation schemes for maximizing the total net benefit of the system and multiple uncertain parameters that have significant influences on the system performance plus their interactions were also identified. Fu et al. (2013) proposed a factorial-based fuzzy-stochastic dynamic programming (FFS-DP) method for tackling multiple uncertainties including fuzziness, randomness and their interaction in reservoir operation management (ROM). The obtained results can help the local authority identify desired water release policies under uncertain system conditions. Significant factors and their interactions were also identified in ROM where results can be further analyzed to generate optimal parameter inputs to obtain maximized system benefits. Furthermore, Wang et al. (2013), Wang and Huang (2013a), and Wang and Huang (2014) developed a number of factorial optimization approaches in water resources management and air pollution control planning, including a sequential factorial analysis (SFA) approach for supporting regional air quality management under uncertainty, a coupled-factorial-analysis-based interval programming (CFA-IP) approach in the application of air quality management, and an integrated approach incorporating an interval linear programming, a two-stage stochastic programming, a chance-constrained programming, Taguchi's orthogonal arrays, and mixed-level factorial design within a general framework for water resources decision-making under interactive and compound uncertainties.

2.5 Literature review summary

During the past decades, numerous efforts were made toward the development of optimization methods to support the planning of environmental management systems. The TSP is effective in dealing with uncertainties which exist in management problems and the related decisions need to be made periodically (Huang and Loucks, 2000). In TSP, a decision is firstly made before values of random variables are known; after the random events have happened and their values are known, a second decision is made in order to take corrective actions following the random events (Huang and Loucks, 2000; Maqsood and Huang, 2003). The CCP is helpful in reflecting risk violation or reliability of satisfying system constraints under uncertainty. It is effective in tackling uncertainties expressed as probability distributions. Moreover, it is effective in dealing with uncertainties that exist in the right-hand-side of the constraints when their probability distributions are available (Morgan et al., 1993). The IMP is effective in dealing with uncertainties which exist in the left-hand-side of the system constraints. This is more advantageous, compared to the conventional method, due to its ability in allowing uncertain parameters to be directly included in the model and communicated into the optimization process. Moreover, the IMP does not lead to more complicated intermediate models, leading to low computational requirements in addressing practical problems. It does not require distributional information since interval numbers were already acceptable as uncertain input parameters (Huang et al., 1992, 1995).

The above proposed methods were often integrated in order to deal with practical problems that are much more complex and may contain dual or multiple uncertainties. However, difficulties still exist in data availability and solution interpretation. Moreover, individual and interactive effects of the uncertain parameters within the system cannot be revealed through the above methods. Therefore, in order to effectively deal with the complexities and uncertainties embedded in the system, as well as to identify which uncertain parameters influence the system the most and to what degree they interact on the system output, more advanced optimization methodologies are required.

CHAPTER 3

A DUAL-INTERVAL TWO-STAGE MIXED-INTEGER INEXACT-CHANCE-CONSTRAINED LINEAR PROGRAMMING METHOD FOR PLANNING FLOOD-DIVERSION MANAGEMENT SYSTEMS UNDER MULTIPLE UNCERTAINTIES

3.1 Background

Floods are a devastating natural event that results adverse impacts on society. Factors such as increased population and their associated activities, which lead to denuded/decreased vegetation cover, deteriorated ecosystems, reduced stream capacity, and increased soil erosion, will have significant effects on the occurrence and intensity of floods. During the 20th century, floods were the number-one natural disaster in the United States in terms of number of lives lost and property damage (Perry, 2000). According to the fact sheet from the USGS, flooding has killed more than 10,000 people since the year of 1900, and the related property damage has being estimated at over $1 billion each year (Perry, 2000). Floodplains are the lowland areas adjacent to a water body and can be used as flood-diversion zones into which floodwater can be diverted and thus reduces the risk of death and property damage. Therefore, sound decision support for floodplain management is essential to achieve practical flood-diversion plans.

In the past decades, floodplain management problems were analyzed through the use of the mixed-integer linear programming (MILP) method (Randall et al., 1997; Watkins et al., 1999; Needham et al., 2000). However, conventional MILP methods are no longer effective in dealing with real-world problems related to floodplain management, due to spatial and temporal variations that exist in system components, such as stream flows, floodplain capacities, and flood-diversion policies. Moreover, the associated costs of flood-diversion patterns and capacity-expansion schemes may also contain uncertain impact factors (Li et al., 2010b). These complexities may be further intensified by the interactions among various uncertain system parameters and the associated economic implications (Maqsood et al., 2005). Therefore, innovative optimization techniques are desired in order to address such problems.

In order to tackle the aforementioned uncertainties and complexities in the planning of flood management systems, extensive inexact optimization techniques have been widely adopted. In general, fuzzy linear programming (FLP), interval linear programming (ILP), and stochastic linear programming (SLP) methods were incorporated into the MILP framework, which led to fuzzy integer programming (FIP), inexact integer programming (IIP), and stochastic integer programming (SIP) (Hillier, 1967; Hamlen, 1980; Keown and Taylor III, 1980; Schultz, 1993; Herrera and Verdegay, 1995; Klein-Haneveld and van der Vlerk, 1999; Ahmed et al., 2004; Saad, 2005; Kong et al., 2006; Escudero et al., 2007; Pandian and Jayalakshmi, 2010). In the IIP method, uncertainties are repressed in the form of interval numbers that are with known lower and upper boundaries (Huang et al., 1992). These interval numbers can be directly incorporated into the optimization process and the related solutions. Therefore, various decision alternatives based on the interpretation of the results can be generated. However, the IIP method may become impractical when parameters on the system constraint's right-hand-side are highly uncertain. Moreover, economic consequences cannot be well reflected when the pre-regulated policies are violated (Li and Huang, 2011).

In fact, the two-stage stochastic programming (TSP) method can be used to effectively analyze flood management problems for two reasons: 1) TSP is able to deal with data that are expressed as probability distributions; 2) TSP is helpful when analysis of policy scenarios is preferred (Huang and Loucks, 2000). In recent years, the TSP method was integrated with FIP, IIP, and SIP methods within a general framework. Such integration will be capable of handling uncertainties expressed as fuzzy, random and interval information in the planning of environmental management systems (Maqsood et al., 2004; Li et al., 2007a; Guo et al., 2010). However, the major shortcoming for the TSP method is that, when planning environmental management systems in the future, it is usually difficult to decide whether the system constraints will be violated.

The chance-constrained programming (CCP) method is effective in reflecting the risk of violating the system constraints under uncertainty (Li et al., 2007b). In CCP, system constraints can be allowed to be satisfied in a proportion of cases with given probabilities (Loucks et al., 1981). Moreover, the CCP method has the ability to tackle uncertainties that exist in the constraints' right-hand sides (b_i) and are expressed as probability distributions.

However, limitations still exist among the above optimization methods. Difficulties may be encountered when the available information is associated with multiple uncertainties which can hardly be represented as simple intervals. In detail, the lower bound and upper bound of many intervals may be still inaccurate, leading to dual-uncertainties of the obtained data. For instance, a safety coefficient (θ) is associated with the excess amount of flood flow which can be written as $[a, b]$. If the information on this factor is highly uncertain and can be only infrequently expressed as probability distributions, the concept of dual interval can be incorporated (Liu and Huang, 2009; Liu et al., 2009). In detail, $\left[[a, c], [d, b]\right]$ is considered as dual interval, where $[a, c]$ and $[d, b]$ represent uncertain lower bound and upper bound of this dual interval (Liu et al., 2009).

Moreover, the tolerable level of constraint-violation risk could be uncertain. However, a simple risk levels (q_i) was often defined in order to represent such implicit information. In fact, for parameter $b_i^{(q_i)}$, uncertainties may exist in q_i (probability of violating constraint i), which correspond to a range of relevant parameter values. Thus, an advanced approach for tackling such interval-valued probability is desired.

Therefore, in regard to the above concerns, this study aims to develop a dual-interval two-stage mixed-integer inexact-chance-constrained linear programming (DITMIC) method for decision-making on the planning of flood management systems under multiple uncertainties. In the proposed DITMIC method, MILP, TSP, CCP, and ILP are integrated within a general framework. Moreover, the concept of dual interval and the concept of an interval-valued probability are incorporated into this optimization process. Thus, the developed DITMIC method can be used to effectively tackle the system constraint's left-hand-side uncertainties that are expressed as intervals and dual intervals. At the same time, the uncertainties on the right-hand-side of the constraint can be addressed by dual representation of interval and probabilistic information. In this case, two aspects of probabilistic information are involved. One is for the probability distribution that is embedded in the two-stage stochastic programming (Huang and Loucks, 2000). The other one is for the chance-constrained programming where the admissible risk of violating the constraints is expressed as an interval-valued probability.

Moreover, the DITMIC method will be used to effectively analyze a number of policy scenarios where different levels of economic penalties are involved. Decision-making on the dynamic features of the planning for capacity-expansion can also be facilitated under multiple uncertain conditions (e.g., interval, dual interval, and stochastic).

3.2 Methodology

3.2.1 Formulation of the DITMIC model

Consider a watershed management problem where floodwater needs to be diverted from a river channel to multiple flood-diversion regions during high flow periods. The river has a restricted water-conveyance level and may overflow during high flow seasons. According to local policies on planning flood management systems, a flood warning level on the river has been pre-regulated, and a fixed flood-diversion amount has also been assigned to each of the diversion regions. These were enacted in order to minimize the risk of floodwater overflowing to densely populated areas. If the water in the river channel is below the pre-regulated warning level, then a regular cost for the flood-diversion is applied. However, when floodwater exceeds the pre-regulated warning level, the adjacent regions will be covered by excess floodwater if no mitigation plan is carried out. Thus, allowing this event entails damages associated with penalties for diverting the excess floodwater. Under the above situation, the total amount of floodwater diverted will be the sum of the fixed diversion target and the excess amount of the water diverted. The goal for decision makers is to devise effective flood-diversion plans and capacity-expansion schemes that minimize system cost while maximizing system safety. Decision on flood-diversion targets (e.g., first-stage decision) need to be made before the uncertain flood flow occurs; when the value of such uncertain flood flow is known, a corrective action (e.g., second-stage decision), known as *recourse*, is then undertaken (Huang and Loucks, 2000; Maqsood and Huang, 2003). Therefore, the problem can be formulated as a two-stage stochastic mixed-integer programming (TMIP) model as follows:

$$\text{Min } f = \sum_{i=1}^{u} C_i\, W_i + \mathrm{E}\left[\sum_{i=1}^{u}[C_i\, T_{iFL} + D_i\, S_{iFL}]\right] + \sum_{i=1}^{u}\sum_{m=1}^{l} EC_{im}\, \Delta R_{im}\, y_{iFLm} \tag{3.1a}$$

subject to:

$$W_i + (1+\theta)\, S_{iFL} \le R_{i\,max},\ \forall i \tag{3.1b}$$

(existing maximum capacity constraints)

$$T_{iFL} \le \sum_{m=1}^{l} \Delta R_{im}\, y_{iFLm}\,,\ \forall i \tag{3.1c}$$

(expanded capacity constraints)

$$\sum_{i=1}^{u}[W_i + (1+\theta)\, S_{iFL} + T_{iFL}] \le \sum_{i=1}^{u} R_{i\,max} + \sum_{i=1}^{u}\sum_{m=1}^{l} \Delta R_{im}\, y_{iFLm},\ \forall i \tag{3.1d}$$

(total diversion capacity constraints)

$$\sum_{i=1}^{u}(W_i + S_{iFL} + T_{iFL}) \ge FL,\ \forall_{FL} \tag{3.1e}$$

(flood flow constraints)

$$y_{iFLm} = \begin{cases} 1, \text{ if floodplain capacity needs to be expanded} \\ 0, \text{ if otherwise} \end{cases},\ \forall i,\ _{FL},\ m \tag{3.1f}$$

(binary constraints for capacity expansion)

$$\sum_{m=1}^{l} y_{iFLm} \le 1,\ \forall i \tag{3.1g}$$

(diversion capacity of region i can be expanded only once with option m)

$W_i \geq 0, \forall i$ (3.1h)

$S_{iFL} \geq 0, \forall i$ (3.1i)

$T_{iFL} \geq 0, \forall i$ (3.1j)

(non-negative constraints)

where,

f: expected system cost (objective-function value) ($)

i: index for flood-diversion region, and $i = 1, 2, \ldots, u$

m: expansion option of diversion capacity, and $m = 1, 2, \ldots, l$

C_i: regular cost per unit of floodwater diverted to region i ($\$/m^3$) (first-stage cost parameter)

W_i: amount of allowable floodwater diverted to region i (m^3) (first-stage decision variable)

$E[\cdot]$: expected value of random variable

T_{iFL}: amount of increased allowance to region i when its diversion capacity is expanded under flood flow level FL (m^3) (the second-stage decision variable)

D_i: penalty per unit of excess amount of floodwater diverted to region i (m^3)

S_{iFL}: amount of excess floodwater diverted to region i when the allowable diversion level is exceeded when the flood flow level is FL (m^3) (the second-stage decision variable)

EC_{im}: capacity expansion cost for region i with option m ($\$/m^3$)

ΔR_{im}: level of capacity expansion option m for region i (m^3)

y_{iFLm}: binary variable indicating the expansion of region i with expansion option m

FL: amount of random flood flow that is available to be diverted (m^3)

$R_{i\,max}$: existing maximum diversion capacity of region i (m^3)

θ: safety coefficient of excess floodwater during peak flood flow

Model (3.1) can reflect flood flow uncertainties that are expressed as probability density functions. For example, constraints of flood flow are uncertain and are expressed as random variables. Nonetheless, when the maximum diversion capacities ($R_{i\,max}$) can be only expressed as a conventional interval, or fuzzy and/or stochastic parameters, due to its highly complicated and uncertain nature as the system's right-hand-side parameter, chance-constrained programming (CCP) can be utilized to tackle such a problem through setting the individual probabilistic constraints on such a random variable (Charnes et al., 1971; Charnes and Cooper, 1983). Thus, this led to the development of a two-stage stochastic mixed-integer chance-constrained programming (TMICP) model:

$$\text{Min } f = \sum_{i=1}^{u} C_i\, W_i + \mathrm{E}\left[\sum_{i=1}^{u} [C_i\, T_{iFL} + D_i\, S_{iFL}]\right] + \sum_{i=1}^{u}\sum_{m=1}^{l} EC_{im}\, \Delta R_{im}\, y_{iFLm} \tag{3.2a}$$

subject to:

$$\Pr\{[W_i + (1+\theta)\, S_{iFL}] \le R_{i\,max}\} \ge 1 - q_i,\ \forall i \tag{3.2b}$$

$$T_{iFL} \le \sum_{m=1}^{l} \Delta R_{im}\, y_{iFLm},\ \forall i \tag{3.2c}$$

$$\Pr\left\{\sum_{i=1}^{u} [W_i + (1+\theta)\, S_{iFL} + T_{iFL}] \le \sum_{i=1}^{u} R_{i\,max} + \sum_{i=1}^{u}\sum_{m=1}^{l} \Delta R_{im}\, y_{iFLm}\right\} \ge 1 - q_i,\ \forall i \tag{3.2d}$$

$$\sum_{i=1}^{u} (W_i + S_{iFL} + T_{iFL}) \ge FL,\ \forall_{FL} \tag{3.2e}$$

$$y_{iFLm} = \begin{cases} 1, \text{ if floodplain capacity needs to be expanded} \\ 0, \text{ if otherwise} \end{cases},\ \forall i,\ _{FL},\ m \tag{3.2f}$$

$$\sum_{m=1}^{l} y_{iFLm} \leq 1, \forall i \tag{3.2g}$$

$$W_i \geq 0, \forall i \tag{3.2h}$$

$$S_{iFL} \geq 0, \forall i \tag{3.2i}$$

$$T_{iFL} \geq 0, \forall i \tag{3.2j}$$

$$0 \leq q_i \leq 1 \tag{3.2k}$$

where q_i signifies an admissible probability of violating the system constraint i. However, this model is still nonlinear. In fact, an assumption of discrete distribution can be adopted in order to have it transformed into a linear model (Huang and Loucks, 2000). The distribution of each of the random flood flows (FL) can be converted into an equivalent set of discrete values (Huang and Loucks, 2000). Let each FL takes values FL_j with probability of p_j (j = 1, 2, …, v), where j denotes the level of the flood flows (Huang and Loucks, 2000). Therefore, we have:

$$\mathrm{E}\left[\sum_{i=1}^{u}[C_i\ T_{iFL} + D_i\ S_{iFL}]\right] = \sum_{i=1}^{u}\sum_{j=1}^{v} p_j\left(C_i\ T_{ij} + D_i\ S_{ij}\right), \forall i, j \tag{3.3}$$

Despite the above mentioned point, the chance constraints can be also converted into linear constraints based on the following equation (Charnes et al., 1971; Charnes and Cooper, 1983):

$$[\Pr(A_i x \leq b_i)] \geq 1 - q_i, A_i \in A, b_i \in B, i = 1, 2, \ldots, m \tag{3.4a}$$

Thus model (3.4a) can be turned into a linear constraint (Charnes et al., 1971; Charnes and Cooper, 1983; Huang, 1998):

$$A_i x \leq b_i^{(q_i)}, \forall i \tag{3.4b}$$

where $b_i^{(q_i)} = F_i^{-1}(q_i)$, given the cumulative distribution function (CDF) of b_i (e.g., $F_i(b_i)$) and the probability of violating the constraint i (e.g., q_i) (Li et al., 2007b). Therefore, model (3.2) can be converted into a linear model (TMICLP) as follows:

$$\text{Min } f = \sum_{i=1}^{u} C_i W_i + \sum_{i=1}^{u}\sum_{j=1}^{v} p_j \left(C_i T_{ij} + D_i S_{ij}\right) + \sum_{i=1}^{u}\sum_{m=1}^{l} EC_{im}\, \Delta R_{im}\, y_{ijm} \tag{3.5a}$$

subject to:

$$W_i + (1+\theta) S_{ij} \le R_{i\,max}^{q_i}, \ \forall i \tag{3.5b}$$

$$T_{ij} \le \sum_{m=1}^{l} \Delta R_{im}\, y_{iFLm}, \ \forall i \tag{3.5c}$$

$$\sum_{i=1}^{u}\left[W_i + (1+\theta) S_{ij} + T_{ij}\right] \le \sum_{i=1}^{u} R_{i\,max}^{q_i} + \sum_{i=1}^{u}\sum_{m=1}^{l} \Delta R_{im}\, y_{ijm}, \ \forall i \tag{3.5d}$$

$$\sum_{i=1}^{u}\left(W_i + S_{ij} + T_{ij}\right) \ge FL_j, \ \forall j \tag{3.5e}$$

$$y_{ijm} = \begin{cases} 1, & \text{if floodplain capacity needs to be expanded} \\ 0, & \text{if otherwise} \end{cases}, \ \forall i, j, m \tag{3.5f}$$

$$\sum_{m=1}^{l} y_{ijm} \le 1, \ \forall i \tag{3.5g}$$

$$W_i \ge 0, \ \forall i \tag{3.5h}$$

$$S_{ij} \ge 0, \ \forall i \tag{3.5i}$$

$$T_{ij} \ge 0, \ \forall i \tag{3.5j}$$

where:

j: level of flood flows, and $j = 1, 2, \ldots, v$

FL_j: quantity of random flood flow to be diverted (m^3)

$R_{i\,max}^{q_i}$: cumulative function of existing maximum diversion capacity of the diversion regions (i) with the probability of violating the constraint being equal to q_i (m^3)

T_{ij}: amount of increased allowance of the floodwater to region i when its diversion capacity is expanded under flood flow level of FL_j with probability p_j (m^3) (the second-stage decision variable)

S_{ij}: amount of excess floodwater diverted to region i when the allowable diversion level is exceeded under flood flow level of FL_j with probability p_j (m^3) (the second-stage decision variable)

Although CCP is effective in dealing with the constraint's right-hand-side uncertainties that are expressed as probability distributions, limitations still exist due to the following reasons. Firstly, CCP is incapable of addressing independent uncertainties in the objective coefficients (Birge and Louveaux, 1988; Infanger, 1994; Zare M and Daneshmand, 1995). Secondly, in real-world problems related to environmental management systems, the obtained information is often of poor quality. In order to address the above concerns, interval parameters are introduced into the TMICLP method in order for the uncertainties to be effectively communicated into the optimization process. For example, the uncertain flood flows are expressed as discrete intervals under various flood flow levels. Moreover, the maximum diversion capacity can be presented as a probability distribution with an interval-valued admissible probability of violating the constraint. Simultaneously, the safety coefficient (θ) of the excess floodwater can be expressed as a dual interval due to the fact that the obtained information on this variable is highly insufficient and/or imprecise and cannot be used to construct probability distribution functions. Therefore, this leads to the formulation of a dual-interval two-stage mixed-integer inexact-chance-constrained linear programming (DITMIC) model as follows:

$$\text{Min } f^{\pm} = \sum_{i=1}^{u} C_i^{\pm} W_i^{\pm} + \sum_{i=1}^{u}\sum_{j=1}^{v} p_j \left(C_i^{\pm} T_{ij}^{\pm} + D_i^{\pm} S_{ij}^{\pm}\right) + \sum_{i=1}^{u}\sum_{m=1}^{l} EC_{im}^{\pm} \Delta R_{im}^{\pm} y_{ijm}^{\pm} \tag{3.6a}$$

subject to:

$$W_i^{\pm} + \left(1 + \left(\theta^{\pm}\right)^{\pm}\right) S_{ij}^{\pm} \le R_{i\,max}^{(q_i^{\pm})}, \forall i \tag{3.6b}$$

$$T_{ij}^{\pm} \le \sum_{m=1}^{l} \Delta R_{im}^{\pm} y_{ijm}^{\pm}, \forall i \tag{3.6c}$$

$$\sum_{i=1}^{u} \left[W_i^{\pm} + \left(1 + \left(\theta^{\pm}\right)^{\pm}\right) S_{ij}^{\pm} + T_{ij}^{\pm}\right] \le \sum_{i=1}^{u} R_{i\,max}^{(q_i^{\pm})} + \sum_{i=1}^{u}\sum_{m=1}^{l} \Delta R_{im}^{\pm} y_{ijm}^{\pm}, \forall i \tag{3.6d}$$

$$\sum_{i=1}^{u} \left(W_i^{\pm} + S_{ij}^{\pm} + T_{ij}^{\pm}\right) \ge FL_j^{\pm}, \forall j \tag{3.6e}$$

$$y_{ijm}^{\pm} = \begin{cases} 1, \text{ if floodplain capacity needs to be expanded} \\ 0, \text{ if otherwise} \end{cases}, \forall i, j, m \tag{3.6f}$$

$$\sum_{m=1}^{l} y_{ijm}^{\pm} \le 1, \forall i \tag{3.6g}$$

$$W_i^{\pm} \ge 0, \forall i \tag{3.6h}$$

$$S_{ij}^{\pm} \ge 0, \forall i \tag{3.6i}$$

$$T_{ij}^{\pm} \ge 0, \forall i \tag{3.6j}$$

where $T_{ij}^{\pm}$ and $S_{ij}^{\pm}$ are non-negative continuous decision variables; $y_{ijm}^{\pm}$ are binary decision variables. $f^{\pm}$, $C_i^{\pm}$, $W_i^{\pm}$, $T_{ij}^{\pm}$, $D_i^{\pm}$, $S_{ij}^{\pm}$, $EC_{im}^{\pm}$, $\Delta R_{im}^{\pm}$, and $y_{ijm}^{\pm}$ are expressed as intervals; $(\theta^{\pm})^{\pm}$ denotes dual interval; $FL_j^{\pm}$ are random variables associated with known distribution functions; $R_{i\,max}^{(q_i^{\pm})}$ represents the maximum diversion capacity of the three regions, where $q_i^{\pm}$ is an interval-valued probability of violating the constraint i. Sign "+"indicates that system parameter or decision variable is at its upper bound, while sign "-"corresponds to the lower bound of a parameter or a decision variable.

3.2.2 Solution method

In model (3.6), $W_i^{\pm}$ is the first-stage variable and should be identified before a random event, such as flood flow levels (e.g., $FL_j^{\pm}$), occur (Huang and Loucks, 2000). Therefore, $W_i^{\pm}$ can be expressed as $W_i^{-} + \Delta W_i\, z_i$ in order to achieve the lowest possible system cost under the allowable flood-diversion target, which is associated with random flood flow levels.

Through incorporating the concept of dual interval on the safety coefficient of the excess flood flow, as well as the concept of an interval-valued probability of violating the system constraint, multiple uncertainties can be easily communicated into the optimization process. According to the concept of dual interval, θ is expressed as $\left[[\theta_a, \theta_c], [\theta_d, \theta_b]\right]$, where $[\theta_a, \theta_c]$ and $[\theta_d, \theta_b]$ are intervals representing the uncertain lower bound and upper bound. A class of random intervals can be chosen from the dual

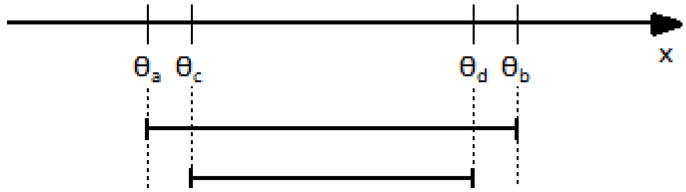

Figure 3.1 Derived possible intervals of the dual interval $\left[[\theta_a, \theta_c], [\theta_d, \theta_b]\right]$

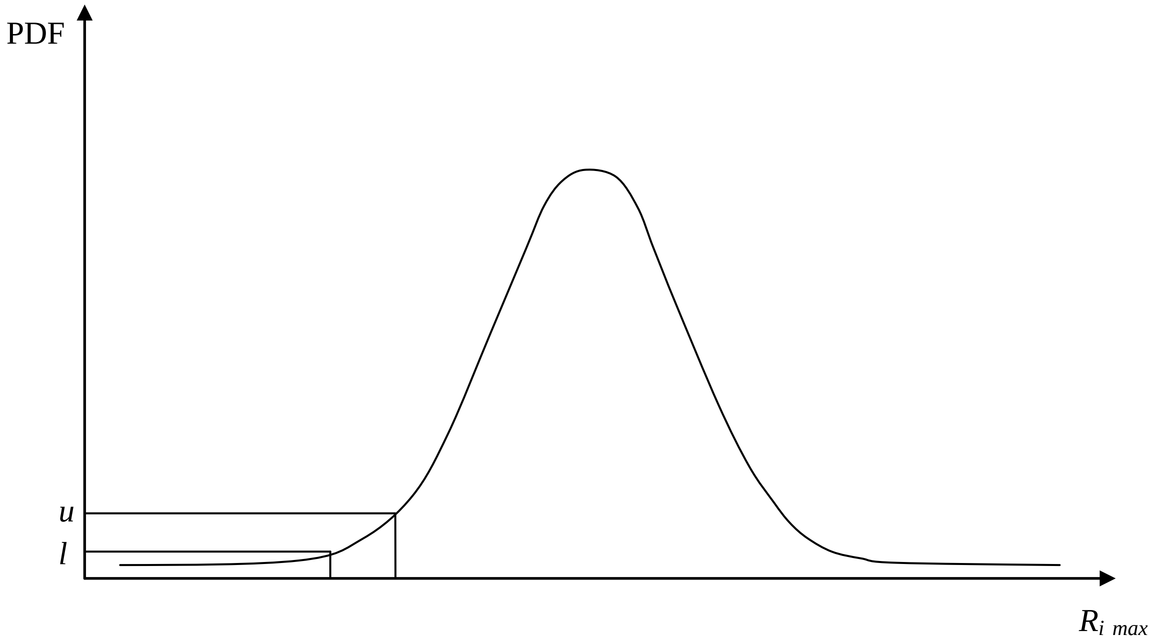

Figure 3.2 An interval-valued probability (l represents the lower bound and u represents the upper bound of the probability)

interval $\left[[\theta_a, \theta_c], [\theta_d, \theta_b]\right]$ (Joslyn, 2003; Liu et al., 2009). Therefore, in consideration of this research, $[\theta_a, \theta_b]$ and $[\theta_c, \theta_d]$ are selected to be the possible intervals with each having a probability of 0.5 as shown in Figure 3.1. Figure 3.2 demonstrates the concept of an interval-valued probability of $R_{i\,max}^{(q_i^{\pm})}$. It is obvious that the uncertainties associated with the interval-valued probability will lead to imprecise values of the maximum capacity of the three diversion regions.

Therefore, model (3.6) can be solved through adopting the Robust Two-Step Method (RTSM) proposed by (Fan and Huang, 2012). In this method, the submodel, $f^{\,+}$, will be solved firstly when the objective function is to be minimized. In this case, $f^{\,+}$ is known as a conservative submodel and corresponds to the upper bound of the objective function. Based on the solutions from the first submodel $(f^{\,+})$, the second submodel, $f^{\,-}$, corresponding to the lower bound of the objective function will then be obtained, and $f^{\,-}$ is an optimistic submodel (Fan and Huang, 2012). Thus, we have:

$$\text{Min } f^{\,+} = \sum_{i=1}^{u} C_i^{+} (W_i^{-} + \Delta W_i \, z_i) + \sum_{i=1}^{u} \sum_{j=1}^{v} p_j \left(C_i^{+} \, T_{ij}^{+} + D_i^{+} \, S_{ij}^{+} \right)$$

$$+ \sum_{i=1}^{u} \sum_{m=1}^{l} EC_{im}^{+} \, \Delta R_{im}^{+} \, y_{ijm}^{+} \tag{3.7a}$$

subject to:

$$(W_i^{-} + \Delta W_i \, z_i) + (1 + \theta^{-}) \, S_{ij}^{+} \leq R_{i\,max}^{(q_i^{-})}, \ \forall i, j \tag{3.7b}$$

$$T_{ij}^{+} \leq \sum_{m=1}^{l} \Delta R_{im}^{+} \, y_{ijm}^{+}, \ \forall i, j \tag{3.7c}$$

$$\sum_{i=1}^{u}\left[(W_i^- + \Delta W_i\, z_i) + (1+\theta^-)\, S_{ij}^+ + T_{ij}^+\right] \le \sum_{i=1}^{u} R_{i\,max}^{(q_i^-)} + \sum_{i=1}^{u}\sum_{m=1}^{l} \Delta R_{im}^+\, y_{ijm}^+ ,\ \forall i, j \tag{3.7d}$$

$$\sum_{i=1}^{u}\left[(W_i^- + \Delta W_i\, z_i) + S_{ij}^+ + T_{ij}^+\right] \ge FL_j^+,\ \forall j \tag{3.7e}$$

$$y_{ijm}^+ = \begin{cases} 1, \text{ if floodplain capacity needs to be expanded} \\ 0, \text{ if otherwise} \end{cases},\ \forall i, j, m \tag{3.7f}$$

$$\sum_{m=1}^{\mathrm{v}} y_{ijm}^+ \le 1,\ \forall i \tag{3.7g}$$

$$W_i^- + \Delta W_i\, z_i \ge 0,\ \forall i \tag{3.7h}$$

$$S_{ij}^+ \ge 0,\ \forall i \tag{3.7i}$$

$$T_{ij}^+ \ge 0,\ \forall i \tag{3.7j}$$

$$0 \le z_i \le 1,\ \forall i \tag{3.7k}$$

where $\Delta W_i = W_i{}^+ - W_i{}^-$ and $z_i \in [0,1]$. f_{opt}^+ is the upper bound of the minimized system cost; $S_{ij\,opt}^+$, $T_{ij\,opt}^+$, $z_{i\,opt}$, and $y_{ijm\,opt}^+$ are solutions obtained from the first submodel (f^+). Moreover, $S_{ij\,opt}^+$, $T_{ij\,opt}^+$, and $z_{i\,opt}$ are continuous variables, whereas $y_{ijm\,opt}^+$ are binary variables. Thus, the second submodel (f^-) can be developed based on the solutions from the first submodel (Fan and Huang, 2012), and we have:

$$\text{Min } f^- = \sum_{i=1}^{u} C_i^- \left(W_i^- + \Delta W_i\, z_{i\,opt}\right) + \sum_{i=1}^{u}\sum_{j=1}^{v} p_j \left(C_i^-\, T_{ij}^- + D_i^-\, S_{ij}^-\right)$$

$$+ \sum_{i=1}^{u}\sum_{m=1}^{l} EC_{im}^-\, \Delta R_{im}^-\, \mathrm{y}_{\mathrm{ijm}}^- \tag{3.8a}$$

subject to:

$$\left(W_i^- + \Delta W_i\, z_{i\,opt}\right) + \left(1 + \theta^+\right) S_{ij}^- \le R_{i\,max}^{(q_i^+)}\,,\ \forall i, j \tag{3.8b}$$

$$T_{ij}^- \le \sum_{m=1}^{l} \Delta R_{im}^-\, y_{ijm}^-\,,\ \forall i, j \tag{3.8c}$$

$$\sum_{i=1}^{u}\left[(W_i^- + \Delta W_i\, z_i) + \left(1 + \theta^+\right) S_{ij}^- + T_{ij}^-\right] \le \sum_{i=1}^{u} R_{i\,max}^{(q_i^+)} + \sum_{i=1}^{u}\sum_{m=1}^{l} \Delta R_{im}^-\, y_{ijm}^-\,,\ \forall i, j \tag{3.8d}$$

$$\sum_{i=1}^{u}\left[(W_i^- + \Delta W_i\, z_i) + S_{ij}^- + T_{ij}^-\right] \ge FL_j^-,\ \forall j \tag{3.8e}$$

$$y_{ijm}^- = \begin{cases} 1, \text{ if floodplain capacity needs to be expanded} \\ \\ 0, \text{ if otherwise} \end{cases},\ \forall i, j, m \tag{3.8f}$$

$$\sum_{m=1}^{v} y_{ijm}^- \le 1,\ \forall i \tag{3.8g}$$

$$S_{ij}^- \le S_{ij\,opt}^+,\ \forall i \tag{3.8h}$$

$$T_{ij}^- \le T_{ij\,opt}^+,\ \forall i \tag{3.8i}$$

$$S_{ij}^- \ge 0,\ \forall i \tag{3.8j}$$

$$T_{ij}^- \ge 0,\ \forall i \tag{3.8k}$$

where f_{opt}^- is the solution of lower bound of the minimized system cost; $S_{ij\,opt}^-$, $T_{ij\,opt}^-$, and $y_{ijm\,opt}^-$ are solutions obtained from the second submodel (f^-). Furthermore, $S_{ij\,opt}^-$ and $T_{ij\,opt}^-$ are continuous variables; $y_{ijm\,opt}^-$ are binary variables. Therefore, the solutions of the DITMIC model are the followings:

$$T_{ij}^{\pm} = \left[T_{ij\,opt}^-,\ T_{ij\,opt}^+\right],\ \forall i, j \tag{3.9a}$$

$$S_{ij}^{\pm} = \left[S_{ij\ opt}^{-}, S_{ij\ opt}^{+}\right], \forall i, j \tag{3.9b}$$

$$y_{ijm\ opt}^{\pm} = \left[y_{ijm\ opt}^{-}, y_{ijm\ opt}^{+}\right], \forall i, j, m \tag{3.9c}$$

$$f_{opt}^{\pm} = \left[f_{opt}^{-}, f_{opt}^{+}\right] \tag{3.9d}$$

The total amount of diverted floodwater can be achieved through adding the allowable diversion target, the incremental amount of floodwater diverted after expansion, and the excess flow after expansion. Thus, we have:

$$N_{ij\ opt}^{\pm} = W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm} + S_{ij\ opt}^{\pm} \tag{3.9e}$$

The above generated results contain solution variables that are expressed as interval numbers for both the objective-function value and the decision variables. As a result, these solution variables can be easily interpreted and multiple decision alternatives can be generated since they are under different levels of risk of violating the constraints. Figure 3.3 presents a schematic illustration on the formation and solution method of the DITMIC method. The detailed solution procedure can be presented as follows:

Step 1: formulate the DITMIC model.

Step 2: transform dual interval parameters into random intervals.

Step 3: reconstruct the DITMIC model into several interval linear programming (ILP) models.

Step 4: transform each of the ILP models into two submodels, where submodel f^{+}, corresponding to the upper bound, is solved firstly.

Step 5: formulate submodel f^{+} containing the objective function and the relevant constraints.

Step 6: solve submodel f^+ and obtain the solutions for $S^+_{ij\,opt}$, $T^+_{ij\,opt}$, $z_{i\,opt}$, $y^+_{ijm\,opt}$ and f^+_{opt} under different q_i levels.

Step 7: formulate submodel f^-containing the objective function and the relevant constraints.

Step 8: solve submodel f^- and obtain the solutions for $S^+_{ij\,opt}$, $T^+_{ij\,opt}$, $y^+_{ijm\,opt}$ and f^-_{opt} under different q_i levels.

Step 9: calculate total amount of the diverted floodwater $N^\pm_{ij\,opt} = W^\pm_{i\,opt} + T^\pm_{ij\,opt} + S^\pm_{ij\,opt}$ under different q_i levels.

Step 10: solution results can be obtained as binary and continuous variables:

$$T^\pm_{ij} = \left[T^-_{ij\,opt}, T^+_{ij\,opt}\right], \forall i, j$$

$$S^\pm_{ij} = \left[S^-_{ij\,opt}, S^+_{ij\,opt}\right], \forall i, j$$

$$y^\pm_{ijm\,opt} = \left[y^-_{ijm\,opt}, y^+_{ijm\,opt}\right], \forall i, j, m$$

$$f^\pm_{opt} = \left[\ f^-_{opt}, f^+_{opt}\right]$$

Step 11: Stop

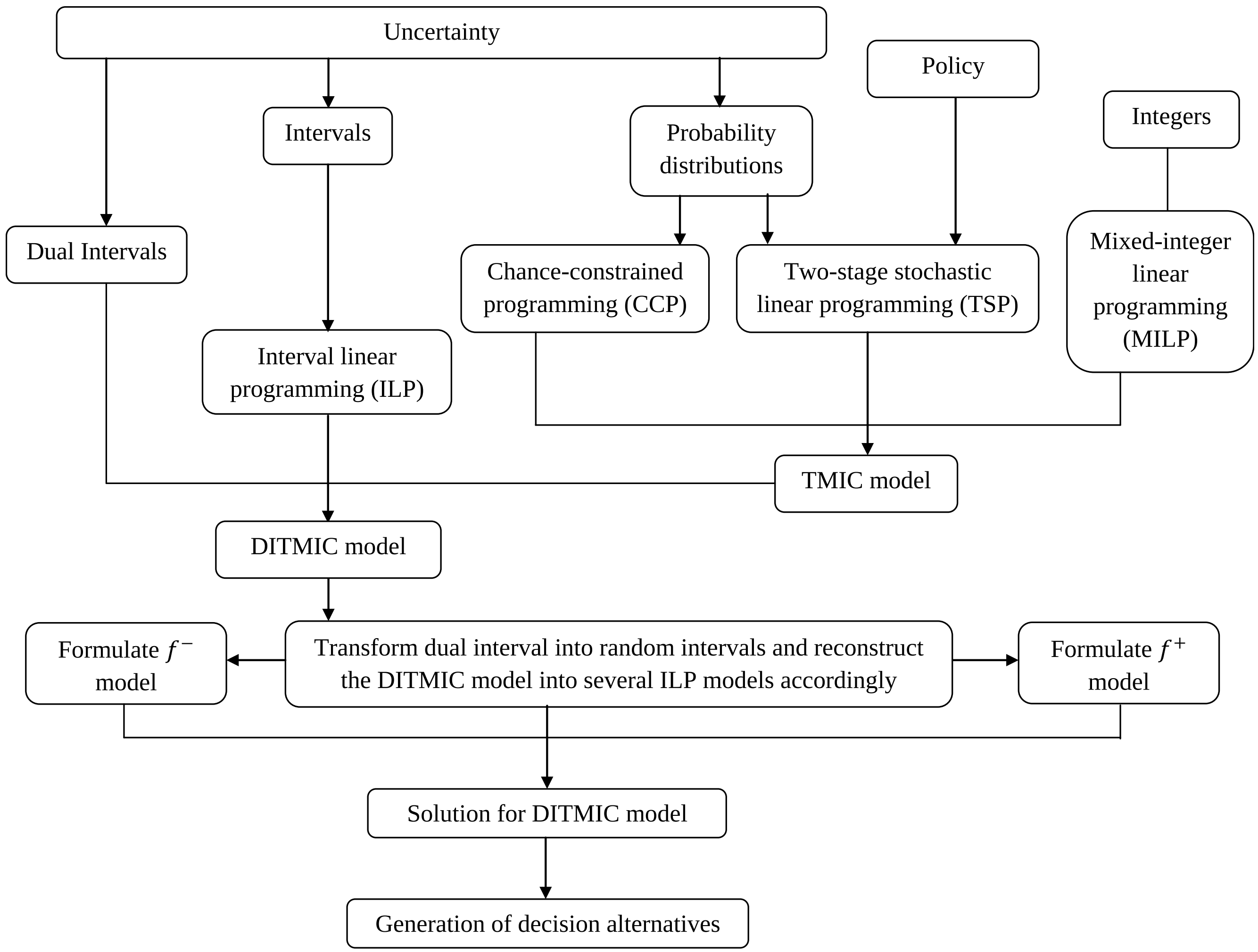

Figure 3.3 Schematic illustration of the formation and solution method of DITMIC model

3.3 Case study

3.3.1 Overview of the study system

The proposed DITMIC method is applied to a study area containing a watershed system and three flood-diversion regions. During flooding seasons, these three regions are ready to serve as floodplains for floodwater diverted from a river channel. As depicted in Figure 3.4, Regions 1, 2, and 3 are located on both sides of a river channel. The river channel has a restricted water-conveyance capacity set by the local authority. If a flood event occurs, the river bank may overflow. According to local policy on flood management, a pre-regulated allowable amount of floodwater is assigned to the regions based on their existing capacities. If the allowance on the amount of floodwater diverted to the regions is not exceeded, regular cost for the diversion will be applied; otherwise, economic penalties or expansion costs will be charged. Usually, economic penalties may contain various aspects such as raised operational costs and increased reconstruction costs. Capacity expansion may help to increase the allowable amount of floodwater diverted to the diversion regions in order to reduce unwanted penalties. Therefore, the total amount of floodwater that is diverted to the regions will be the sum of the amount of allowable floodwater that is initially assigned to the regions, the incremental amount of floodwater when the regions are expanded, and the surplus amount of floodwater after the expansion of the regions.

In this study system, the flood flow levels are random variables and are expressed as intervals (Table 3.1). They vary between different levels of the flood flow ranging from very-low to very-high. The flood flow levels are associated with probability of occurrence. Table 3.2 shows the allowable flood-diversion target, the maximum diversion

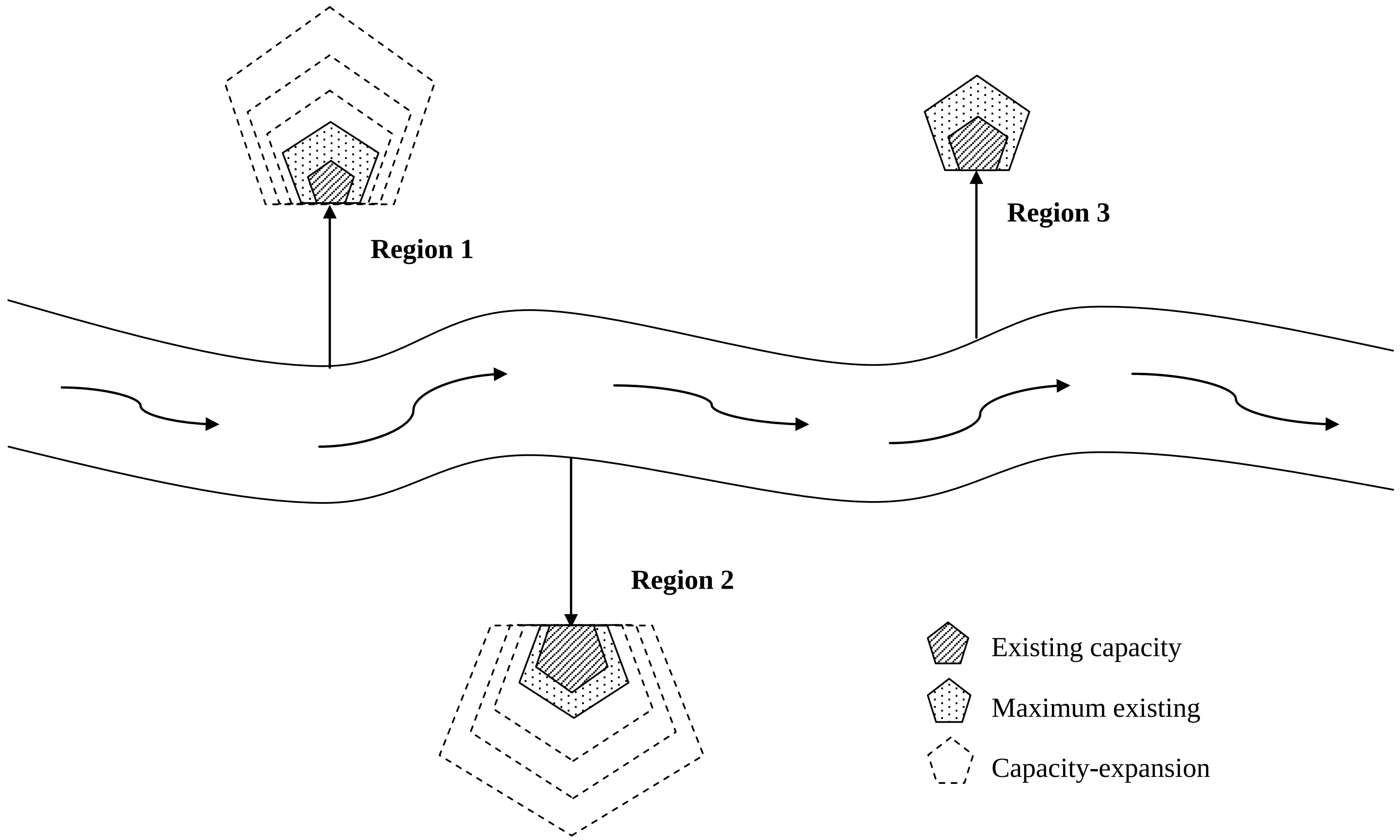

Figure 3.4 Study system of flood-diversion regions

capacity, as well as the associated costs for regular floodwater diversion and penalties for excess floodwater diversion; they are all expressed as interval values. The maximum diversion capacity for each of the three regions is explained in Table 3.3. Table 3.4 contains the safety coefficient that is related to the diversion of the excess amount of floodwater after the regions are expanded; it is expressed as dual interval. Table 3.5 provides the information on capacity-expansion of the three regions and the associated capacity-expansion cost. As indicated by the local policy on flood management, Region 1 can only be expanded once by any of the three capacity-expansion options with a maximum capacity-expansion of $[5, 7]\times10^6$ m^3; similarly, Region 2 is also allowed to be expanded only once with a maximum capacity-expansion of $[6.5, 9]\times10^6$ m^3. Region 3 is prohibited from being expanded due to highly intensified human activities. As a result, the problems under consideration are: 1) how to identify optimal capacity-expansion schemes for the three flood-diversion regions, 2) how to effectively divert floodwater to those three regions when a flood event occurs, 3) how to achieve minimum system cost, and 4) how to reflect flood management policies with the least risk of system disruptions. Since multiple uncertainties exist in various system components and pre-regulated policies need to be upheld, the proposed DITMIC method will efficiently meet these flood-diversion management parameters.

Table 3.1 Flood flow levels

Flood flow levels (i)	Probability of occurrence (p_j) (%)	Amount of flood flows (10^6 m^3)
Very-low	5	[0.5, 1.5]
Low	10	[2.0, 4.0]
Low-medium	15	[5.5, 7.5]
Medium	40	[8.0, 11.0]
Medium-high	15	[11.0, 14.0]
High	10	[14.0, 22.5]
Very-high	5	[23.5, 29.0]

Table 3.2 Maximum diversion capacity, allowable diversion target and the associated costs

Activity	Flood-diversion region		
	i = 1	i = 2	i = 3
Maximum diversion capacity ($R_{i\,max}^{\pm}$) (10^6 m^3)	N(8.3, 2^2)	N(11.9, 2^2)	N(4.5, 0.2^2)
Allowable flood diversion target ($W_i^{\pm}$) (10^6 m^3)	[1.8, 2.9]	[4.2, 5.7]	[2.5, 3.5]
Regular cost for flood-diversion ($C_i^{\pm}$) ($/m^3)	[80, 100]	[90, 110]	[100, 130]
Penalty for flood-diversion ($D_i^{\pm}$) ($/m^3)	[200, 250]	[150, 180]	[180, 210]

Table 3.3 Maximum diversion capacity for the three regions under different risk levels

Region (i)	Maximum diversion capacity (10^6 m^3)	Risk level		
		q = [0.009, 0.011]	q = [0.04, 0.06]	q = [0.09, 0.11]
i = 1	N(8.3, 2^2)	[3.57, 3.72]	[4.80, 5.19]	[5.62, 5.85]
i = 2	N(11.9, 2^2)	[7.17, 7.23]	[8.40, 8.79]	[9.22, 9.45]
i = 3	N(4.5, 0.2^2)	[4.03, 4.04]	[4.15, 4.19]	[4.23, 4.25]

Table 3.4 Safety coefficient of flood diversion

Safety coefficient (θ)
[[0.09, 0.11], [0.19, 0.21]]

Table 3.5 Capacity-expansion options and the related costs

Diversion region (i)	i = 1	i = 2	i = 3
Capacity-expansion option (10^6 m^3)			
$\Delta R_{i1}^{\pm}$ (option 1)	[3, 5]	[4.5, 7]	0
$\Delta R_{i2}^{\pm}$ (option 2)	[4, 6]	[5.5, 8]	0
$\Delta R_{i3}^{\pm}$ (option 3)	[5, 7]	[6.5, 9]	0
Capacity-expansion cost ($/$m^3$)			
$EC_{i1}^{\pm}$ (option 1)	60	90	0
$EC_{i2}^{\pm}$ (option 2)	70	100	0
$EC_{i3}^{\pm}$ (option 3)	80	110	0

3.3.2 Result analysis

Table 3.6 shows the binary results obtained from the proposed DITMIC method under a set of interval-valued probability levels ($q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$) when the safety coefficient (θ) of the excess floodwater equals $\left[[0.09, 0.11], [0.19, 0.21]\right]$. As indicated in the table, Region 1 needs to be expanded to meet a very-high level of the flood flow when $q = [0.009, 0.011]$; when $q = [0.04, 0.06]$ and $[0.09, 0.11]$, Region 1 would be expanded to match high and very-high levels of the flood flow. In addition, Region 2 would be expanded under high and very-high flood flow levels when $q = [0.009, 0.011]$; when $q = [0.04, 0.06]$ and $[0.09, 0.11]$, Region 2 needs a capacity-expansion during a very-high level of the flood flow. The binary variables are expressed as intervals which correspond to the lower bound and upper bound of the objective-function value. Under advantageous conditions, the lower bound of the capacity-expansion option would be chosen in order to achieve lower system cost. In comparison, the upper bound of the capacity-expansion option would be needed when worse-case conditions are considered. Region 3 should not be expanded under any of the flood flow levels. Table 3.6 and Figures 3.5 to 3.7 delineate detailed capacity-expansion schemes for Region 1 under a set of interval-valued probability levels. For instance, when $q = [0.009, 0.011]$, Region 1 would not be expanded under very-low to high flood flow levels with probability of occurrence ranging from 5% to 40%. However, under a very-high flood flow level when the probability of occurrence is 5%, Region 1 needs to be expanded. When $q = [0.04, 0.06]$ and $[0.09, 0.11]$, no expansion would be required for Region 1 under very-low to medium-high flood flow levels with a probability of

Table 3.6 Binary solutions of the DITMIC method

Flow levels (j)	Probability of occurrence (%)	Expansion options ($\Delta R_{im}^{\pm}$)	Symbol		Solutions					
					Risk levels					
					q = [0.009, 0.011]		q = [0.04, 0.06]		q = [0.09, 0.11]	
			Region 1	Region 2	Region 1	Region 2	Region 1	Region 2	Region 1	Region 2
Very-low	5	1	$y_{111}^{\pm}$	$y_{211}^{\pm}$	0	0	0	0	0	0
Very-low	5	2	$y_{112}^{\pm}$	$y_{212}^{\pm}$	0	0	0	0	0	0
Very-low	5	3	$y_{113}^{\pm}$	$y_{213}^{\pm}$	0	0	0	0	0	0
Low	10	1	$y_{121}^{\pm}$	$y_{221}^{\pm}$	0	0	0	0	0	0
Low	10	2	$y_{122}^{\pm}$	$y_{222}^{\pm}$	0	0	0	0	0	0
Low	10	3	$y_{123}^{\pm}$	$y_{223}^{\pm}$	0	0	0	0	0	0
Low-medium	15	1	$y_{131}^{\pm}$	$y_{231}^{\pm}$	0	0	0	0	0	0
Low-medium	15	2	$y_{132}^{\pm}$	$y_{232}^{\pm}$	0	0	0	0	0	0
Low-medium	15	3	$y_{133}^{\pm}$	$y_{233}^{\pm}$	0	0	0	0	0	0
Medium	40	1	$y_{141}^{\pm}$	$y_{241}^{\pm}$	0	0	0	0	0	0

Table 3.6 (Cont.)

Flow levels (j)	Probability of occurrence (%)	Expansion options ($\Delta R_{im}^{\pm}$)	Symbol		Solutions					
					Risk levels					
					q = [0.009, 0.011]		q = [0.04, 0.06]		q = [0.09, 0.11]	
			Region 1	Region 2	Region 1	Region 2	Region 1	Region 2	Region 1	Region 2
Medium	40	2	$y_{142}^{\pm}$	$y_{242}^{\pm}$	0	0	0	0	0	0
Medium	40	3	$y_{143}^{\pm}$	$y_{243}^{\pm}$	0	0	0	0	0	0
Medium-high	15	1	$y_{151}^{\pm}$	$y_{251}^{\pm}$	0	0	0	0	0	0
Medium-high	15	2	$y_{152}^{\pm}$	$y_{252}^{\pm}$	0	0	0	0	0	0
Medium-high	15	3	$y_{153}^{\pm}$	$y_{253}^{\pm}$	0	0	0	0	0	0
High	10	1	$y_{161}^{\pm}$	$y_{261}^{\pm}$	0	0	0	0	[0, 1]	0
High	10	2	$y_{162}^{\pm}$	$y_{262}^{\pm}$	0	[0, 1]	[0, 1]	0	0	0
High	10	3	$y_{163}^{\pm}$	$y_{263}^{\pm}$	0	0	0	0	0	0

Table 3.6 (Cont.)

Flow levels (j)	Probability of occurrence (%)	Expansion options ($\Delta R_{im}^{\pm}$)	Symbol		Solutions					
					Risk levels					
					q = [0.009, 0.011]		q = [0.04, 0.06]		q = [0.09, 0.11]	
			Region 1	Region 2	Region 1	Region 2	Region 1	Region 2	Region 1	Region 2
Very-high	5	1	$y_{171}^{\pm}$	$y_{271}^{\pm}$	0	0	0	[1, 1]	[1, 1]	[1, 1]
Very-high	5	2	$y_{172}^{\pm}$	$y_{272}^{\pm}$	0	[1, 1]	[1, 1]	0	0	0
Very-high	5	3	$y_{173}^{\pm}$	$y_{273}^{\pm}$	[1, 1]	0	0	0	0	0

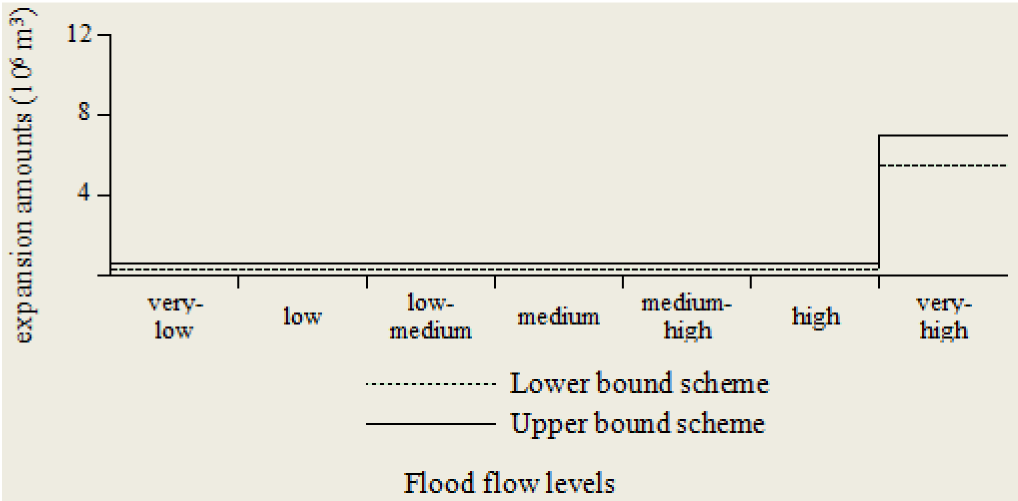

Figure 3.5 Capacity expansion for region 1 when $q = [0.009, 0.011]$ and $\theta = [0.09, 0.21]$

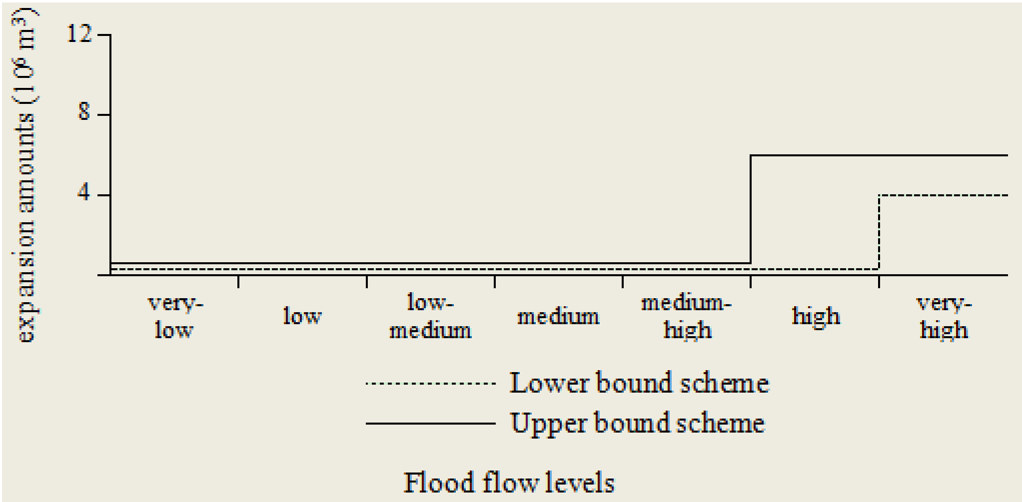

Figure 3.6 Capacity expansion for region 1 when $q = [0.04, 0.06]$ and $\theta = [0.09, 0.21]$

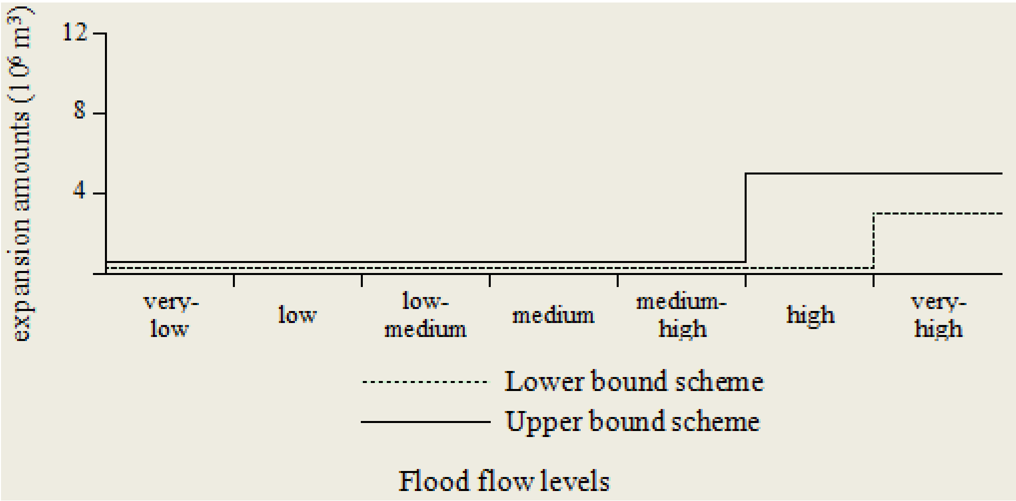

Figure 3.7 Capacity expansion for region 1 when $q = [0.09, 0.11]$ and $\theta = [0.09, 0.21]$

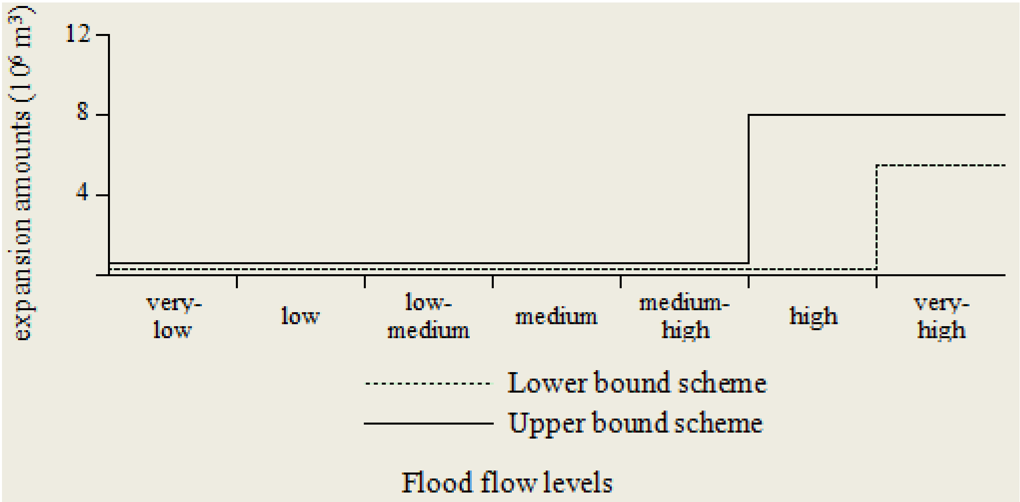

Figure 3.8 Capacity expansion for region 2 when $q = [0.009, 0.011]$ and $\theta = [0.11, 0.19]$

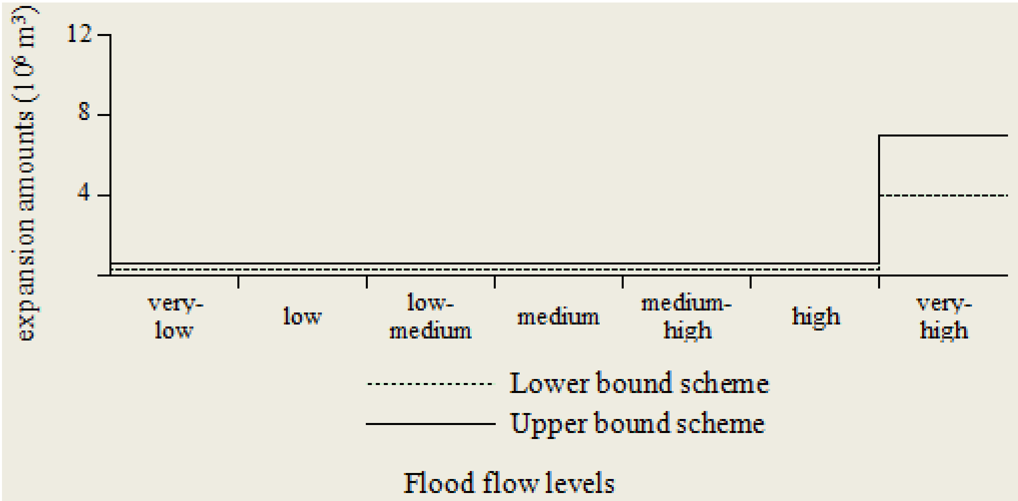

Figure 3.9 Capacity expansion for region 2 when $q = [0.04, 0.06]$ and $\theta = [0.11, 0.19]$

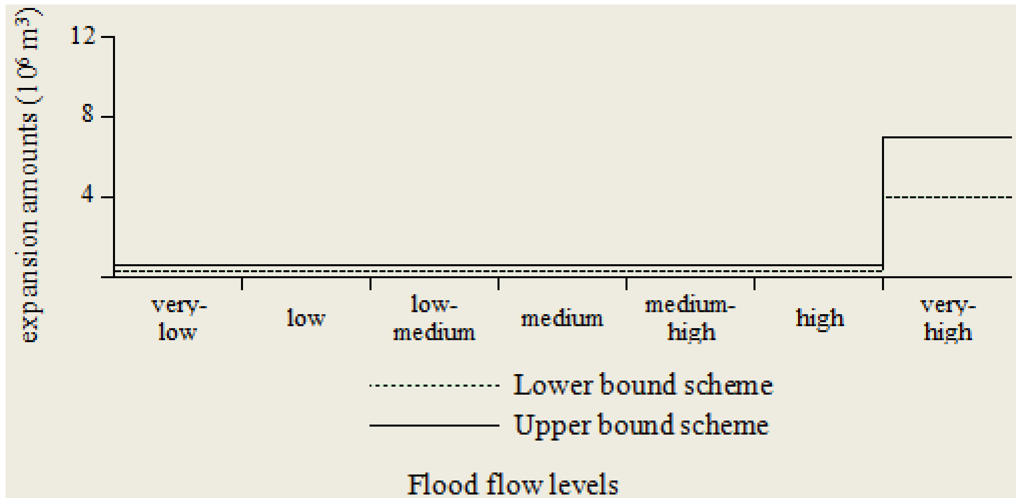

Figure 3.10 Capacity expansion for region 2 when $q = [0.09, 0.11]$ and $\theta = [0.11, 0.19]$

occurrence between 5% and 40%. Figures 3.8 to 3.10 outlined the detailed capacity-expansion schemes for Region 2 under different risk levels ($q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$), with flood flow levels ranging from very-low to very-high.

Tables 3.7 to 3.12 represent the continuous variable solutions from the DITMIC method. They contain both the first-stage and second-stage variables. $W_i^{\pm}$ is the first-stage variable. It signifies the allowable flood-diversion amount which is pre-regulated by the local authority. $T_{ij}^{\pm}$ is the second-stage variable. It denotes the augmented amount of floodwater being diverted and it is associated with the expansion-capacity. $S_{ij}^{\pm}$ is the second-stage variable. It stands for the amount of excess floodwater controlled by the maximum diversion capacity. During floods, an allowable amount of floodwater is to be diverted to the assigned three regions; if the floodwater still exceeds the pre-regulated level, the incremental amount or the excess amount of such floodwater will be diverted. Accordingly, the total amount of the floodwater being diverted would be calculated by adding the allowable diversion, the incremental diversion, and the excess diversion (e.g., $N_{ij}^{\pm} = W_i^{\pm} + T_{ij}^{\pm} + S_{ij}^{\pm}$).

The solutions of $z_{1\,opt} = 1.00$, $z_{2\,opt} = 1.00$, and $z_{3\,opt} = 0.46$, when $\theta = [0.09, 021]$, indicate that the amount of allowable floodwater diversion ($W_i^{\pm} = W_i^{-} + \Delta W_i\, z_{i\,opt}$) for Regions 1 to 3 would be 2.90×10^6 m^3, 5.70×10^6 m^3, and 2.96×10^6 m^3 with q level equals $[0.009, 0.011]$; however, when $q = [0.04, 0.06]$ and $[0.09, 0.11]$, this amount would be 2.90×10^6 m^3 ($z_{1\,opt} = 1.00$), 5.60×10^6 m^3 ($z_{2\,opt} = 0.93$) and 2.50×10^6 m^3 ($z_{3\,opt} = 0.00$) for the three regions. In comparison, under a situation where $\theta = [0.11, 019]$, $z_{1\,opt} = 1.00$,

Table 3.7 Solutions of continuous variables under q = [0.009, 0.011] when θ = [0.09, 0.21]

			Flood-diversion pattern $(10^6 \mathrm{m}^3)$				
Flood flow level (j)	Probability (%)	Region (i)	$W_{i\,opt}^{\pm}$	$T_{ij\,opt}^{\pm}$	$S_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm} + S_{ij\,opt}^{\pm}$
Very-low	5	1	2.90	0	0	2.90	2.90
Very-low	5	2	5.70	0	0	5.70	5.70
Very-low	5	3	2.96	0	0	2.96	2.96
Low	10	1	2.90	0	0	2.90	2.90
Low	10	2	5.70	0	0	5.70	5.70
Low	10	3	2.96	0	0	2.96	2.96
Low-medium	15	1	2.90	0	0	2.90	2.90
Low-medium	15	2	5.70	0	0	5.70	5.70
Low-medium	15	3	2.96	0	0	2.96	2.96
Medium	40	1	2.90	0	0	2.90	2.90
Medium	40	2	5.70	0	0	5.70	5.70
Medium	40	3	2.96	0	0	2.96	2.96

Table 3.7 (Cont.)

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6 m^3)$				
			$W_{i\,opt}^{\pm}$	$T_{ij\,opt}^{\pm}$	$S_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm} + S_{ij\,opt}^{\pm}$
Medium-high	15	1	2.90	0	[0, 0.11]	2.90	[2.90, 3.01]
Medium-high	15	2	5.70	0	[0, 1.35]	5.70	[5.70, 7.05]
Medium-high	15	3	2.96	0	[0, 0.98]	2.96	[2.96, 3.94]
High	10	1	2.90	0	[0.21, 0.61]	2.90	[3.11, 3.51]
High	10	2	5.70	[0, 8]	[1.34, 1.35]	[5.70, 13.70]	[7.04, 15.05]
High	10	3	2.96	0	[0.89, 0.98]	2.96	[3.85, 3.94]
Very-high	5	1	2.90	[5, 7]	[0, 0.11]	[7.90, 9.90]	[7.90, 10.01]
Very-high	5	2	5.70	[5.5, 8]	[1.34, 1.35]	[11.20, 13.70]	[12.54, 15.05]
Very-high	5	3	2.96	0	[0.10, 0.98]	2.96	[3.06, 3.94]

Decision variables: $z_{1\,opt} = 1.00$, $z_{2\,opt} = 1.00$, $z_{3\,opt} = 0.46$

System cost (10^6): $f_{opt}^{\pm} = [2087.18, 3784.40]$

Table 3.8 Solutions of continuous variables under q = [0.04, 0.06] when θ = [0.09, 0.21]

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6\mathrm{m}^3)$				
			$W^{\pm}_{i\,opt}$	$T^{\pm}_{ij\,opt}$	$S^{\pm}_{ij\,opt}$	$W^{\pm}_{i\,opt}+T^{\pm}_{ij\,opt}$	$W^{\pm}_{i\,opt}+T^{\pm}_{ij\,opt}+S^{\pm}_{ij\,opt}$
Very-low	5	1	2.90	0	0	2.90	2.90
Very-low	5	2	5.60	0	0	5.60	5.60
Very-low	5	3	2.50	0	0	2.50	2.50
Low	10	1	2.90	0	0	2.90	2.90
Low	10	2	5.60	0	0	5.60	5.60
Low	10	3	2.50	0	0	2.50	2.50
Low-medium	15	1	2.90	0	0	2.90	2.90
Low-medium	15	2	5.60	0	0	5.60	5.60
Low-medium	15	3	2.50	0	0	2.50	2.50
Medium	40	1	2.90	0	0	2.90	2.90
Medium	40	2	5.60	0	0	5.60	5.60
Medium	40	3	2.50	0	0	2.50	2.50

Table 3.8 (Cont.)

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6 m^3)$				
			$W_{i\,opt}^{\pm}$	$T_{ij\,opt}^{\pm}$	$S_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm} + S_{ij\,opt}^{\pm}$
Medium-high	15	1	2.90	0	0	2.90	2.90
Medium-high	15	2	5.60	0	[0, 2.57]	5.60	[5.60, 8.17]
Medium-high	15	3	2.50	0	[0, 0.43]	2.50	[2.50, 2.93]
High	10	1	2.90	[0, 6]	[0, 1.42]	[2.90, 8.90]	[2.90, 10.32]
High	10	2	5.60	0	2.57	5.60	8.17
High	10	3	2.50	0	[0.43, 1.51]	2.50	[2.93, 4.01]
Very-high	5	1	2.90	[4, 6]	[0.04, 0.92]	[6.90, 8.90]	[6.94, 9.82]
Very-high	5	2	5.60	[4.5, 7]	2.57	[10.10, 12.60]	[12.57, 15.17]
Very-high	5	3	2.50	0	[1.40, 1.51]	2.50	[3.90, 4.01]
Decision variables: $z_{1\,opt} = 1.00$, $z_{2\,opt} = 0.93$, $z_{3\,opt} = 0.00$							
System cost (10^6): $f_{opt}^{\pm} = [1785.73, 3076.41]$							

Table 3.9 Solutions of continuous variables under q = [0.09, 0.11] when θ = [0.09, 0.21]

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern (10^6m^3)				
			$W_{i\,opt}^{\pm}$	$T_{ij\,opt}^{\pm}$	$S_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm} + S_{ij\,opt}^{\pm}$
Very-low	5	1	2.90	0	0	2.90	2.90
Very-low	5	2	5.60	0	0	5.60	5.60
Very-low	5	3	2.50	0	0	2.50	2.50
Low	10	1	2.90	0	0	2.90	2.90
Low	10	2	5.60	0	0	5.60	5.60
Low	10	3	2.50	0	0	2.50	2.50
Low-medium	15	1	2.90	0	0	2.90	2.90
Low-medium	15	2	5.60	0	0	5.60	5.60
Low-medium	15	3	2.50	0	0	2.50	2.50
Medium	40	1	2.90	0	0	2.90	2.90
Medium	40	2	5.60	0	0	5.60	5.60
Medium	40	3	2.50	0	0	2.50	2.50

Table 3.9 (Cont.)

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6 \mathrm{m}^3)$				
			$W_{i\ opt}^{\pm}$	$T_{ij\ opt}^{\pm}$	$S_{ij\ opt}^{\pm}$	$W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm}$	$W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm} + S_{ij\ opt}^{\pm}$
Medium-high	15	1	2.90	0	0	2.90	2.90
Medium-high	15	2	5.60	0	[0, 3.00]	5.60	[5.60, 8.60]
Medium-high	15	3	2.50	0	0	2.50	2.50
High	10	1	2.90	[0, 5]	[0, 1.59]	[2.90, 7.90]	[2.90, 9.49]
High	10	2	5.60	0	[3.00, 3.32]	5.60	[8.60, 8.92]
High	10	3	2.50	0	[0, 1.59]	2.50	[2.50, 4.09]
Very-high	5	1	2.90	[3, 5]	[0.37, 1.09]	[5.90, 7.90]	[6.27, 8.99]
Very-high	5	2	5.60	[4.5, 7]	[3.18, 3.32]	[10.10, 12.60]	[13.28, 15.92]
Very-high	5	3	2.50	0	[1.45, 1.59]	2.50	[3.95, 4.09]

Decision variables: $z_{1\ opt} = 1.00$, $z_{2\ opt} = 0.93$, $z_{3\ opt} = 0.00$

System cost (10^6): $f_{opt}^{\pm} = [1688.85, 2848.61]$

Table 3.10 Solutions of continuous variables under q = [0.009, 0.011] when θ = [0.11, 0.19]

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $\left(10^6\mathrm{m}^3\right)$				
			$W_{i\ opt}^{\pm}$	$T_{ij\ opt}^{\pm}$	$S_{ij\ opt}^{\pm}$	$W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm}$	$W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm} + S_{ij\ opt}^{\pm}$
Very-low	5	1	2.90	0	0	2.90	2.90
Very-low	5	2	5.70	0	0	5.70	5.70
Very-low	5	3	3.50	0	0	3.50	3.50
Low	10	1	2.90	0	0	2.90	2.90
Low	10	2	5.70	0	0	5.70	5.70
Low	10	3	3.50	0	0	3.50	3.50
Low-medium	15	1	2.90	0	0	2.90	2.90
Low-medium	15	2	5.70	0	0	5.70	5.70
Low-medium	15	3	3.50	0	0	3.50	3.50
Medium	40	1	2.90	0	0	2.90	2.90
Medium	40	2	5.70	0	0	5.70	5.70
Medium	40	3	3.50	0	0	3.50	3.50

Table 3.10 (Cont.)

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6 \mathrm{m}^3)$				
			$W^{\pm}_{i\ opt}$	$T^{\pm}_{ij\ opt}$	$S^{\pm}_{ij\ opt}$	$W^{\pm}_{i\ opt} + T^{\pm}_{ij\ opt}$	$W^{\pm}_{i\ opt} + T^{\pm}_{ij\ opt} + S^{\pm}_{ij\ opt}$
Medium-high	15	1	2.90	0	[0, 0.10]	2.90	[2.90, 3.0]
Medium-high	15	2	5.70	0	[0, 1.32]	5.70	[5.70, 7.02]
Medium-high	15	3	3.50	0	[0, 0.48]	3.50	[3.50, 3.98]
High	10	1	2.90	0	[0.12, 0.60]	2.90	[3.02, 3.50]
High	10	2	5.70	[0, 8]	1.32	[5.70, 13.70]	[7.02, 15.02]
High	10	3	3.50	0	[0.46, 0.48]	3.50	[3.96, 3.98]
Very-high	5	1	2.90	[5, 7]	[0, 0.10]	[7.90, 9.90]	[7.90, 10.00]
Very-high	5	2	5.70	[5.5, 8]	[0.90, 1.32]	[11.20, 13.70]	[12.10, 15.02]
Very-high	5	3	3.50	0	[0, 0.48]	3.50	[3.50, 3.98]

Decision variables: $z_{1\ opt} = 1.00$, $z_{2\ opt} = 1.00$, $z_{3\ opt} = 1.00$

System cost (10^6): $f^{\pm}_{opt} = [2126.70, 3820.28]$

Table 3.11 Solutions of continuous variables under q = [0.04, 0.06] when θ = [0.11, 0.19]

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $\left(10^6\mathrm{m}^3\right)$				
			$W_{i\,opt}^{\pm}$	$T_{ij\,opt}^{\pm}$	$S_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm} + S_{ij\,opt}^{\pm}$
Very-low	5	1	2.90	0	0	2.90	2.90
Very-low	5	2	5.60	0	0	5.60	5.60
Very-low	5	3	2.50	0	0	2.50	2.50
Low	10	1	2.90	0	0	2.90	2.90
Low	10	2	5.60	0	0	5.60	5.60
Low	10	3	2.50	0	0	2.50	2.50
Low-medium	15	1	2.90	0	0	2.90	2.90
Low-medium	15	2	5.60	0	0	5.60	5.60
Low-medium	15	3	2.50	0	0	2.50	2.50
Medium	40	1	2.90	0	0	2.90	2.90
Medium	40	2	5.60	0	0	5.60	5.60
Medium	40	3	2.50	0	0	2.50	2.50

Table 3.11 (Cont.)

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern (10^6m^3)				
			$W_{i\,opt}^{\pm}$	$T_{ij\,opt}^{\pm}$	$S_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm}$	$W_{i\,opt}^{\pm} + T_{ij\,opt}^{\pm} + S_{ij\,opt}^{\pm}$
Medium-high	15	1	2.90	0	0	2.90	2.90
Medium-high	15	2	5.60	0	[0, 2.52]	5.60	[5.60, 8.60]
Medium-high	15	3	2.50	0	[0, 0.48]	2.50	[2.50, 2.98]
High	10	1	2.90	[0, 6]	[0, 1.49]	[2.90, 8.90]	[2.90, 10.39]
High	10	2	5.60	0	2.52	5.60	8.12
High	10	3	2.50	0	[0.48, 1.49]	2.50	[2.98, 3.99]
Very-high	5	1	2.90	[4, 6]	[0.06, 0.99]	[6.90, 8.90]	[6.96, 9.89]
Very-high	5	2	5.60	[4.5, 7]	2.52	[10.10, 12.60]	[12.62, 15.12]
Very-high	5	3	2.50	0	[1.42, 1.49]	2.50	[3.92, 3.99]

Decision variables: $z_{1\,opt} = 1.00$, $z_{2\,opt} = 0.93$, $z_{3\,opt} = 0.00$

System cost (10^6): $f_{opt}^{\pm} = [1785.96, 3077.26]$

Table 3.12 Solutions of continuous variables under q = [0.09, 0.11] when θ = [0.11, 0.19]

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6 m^3)$				
			$W^{\pm}_{i\,opt}$	$T^{\pm}_{ij\,opt}$	$S^{\pm}_{ij\,opt}$	$W^{\pm}_{i\,opt} + T^{\pm}_{ij\,opt}$	$W^{\pm}_{i\,opt} + T^{\pm}_{ij\,opt} + S^{\pm}_{ij\,opt}$
Very-low	5	1	2.90	0	0	2.90	2.90
Very-low	5	2	5.60	0	0	5.60	5.60
Very-low	5	3	2.50	0	0	2.50	2.50
Low	10	1	2.90	0	0	2.90	2.90
Low	10	2	5.60	0	0	5.60	5.60
Low	10	3	2.50	0	0	2.50	2.50
Low-medium	15	1	2.90	0	0	2.90	2.90
Low-medium	15	2	5.60	0	0	5.60	5.60
Low-medium	15	3	2.50	0	0	2.50	2.50
Medium	40	1	2.90	0	0	2.90	2.90
Medium	40	2	5.60	0	0	5.60	5.60
Medium	40	3	2.50	0	0	2.50	2.50

Table 3.12 (Cont.)

Flood flow level (j)	Probability (%)	Region (i)	Flood-diversion pattern $(10^6 m^3)$				
			$W_{i\ opt}^{\pm}$	$T_{ij\ opt}^{\pm}$	$S_{ij\ opt}^{\pm}$	$W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm}$	$W_{i\ opt}^{\pm} + T_{ij\ opt}^{\pm} + S_{ij\ opt}^{\pm}$
Medium-high	15	1	2.90	0	0	2.90	2.90
Medium-high	15	2	5.60	0	[0, 3.00]	5.60	[5.60, 8.60]
Medium-high	15	3	2.50	0	0	2.50	2.50
High	10	1	2.90	[0, 5]	[0, 1.68]	[2.90, 7.90]	[2.90, 9.58]
High	10	2	5.60	0	[3.00, 3.26]	5.60	[8.60, 8.86]
High	10	3	2.50	0	[0, 1.56]	2.50	[2.50, 4.06]
Very-high	5	1	2.90	[3, 5]	[0.29, 1.18]	[5.90, 7.90]	[6.19, 9.08]
Very-high	5	2	5.60	[4.5, 7]	[3.23, 3.26]	[10.10, 12.60]	[13.33, 15.86]
Very-high	5	3	2.50	0	[1.47, 1.56]	2.50	[3.97, 4.06]
Decision variables: $z_{1\ opt} = 1.00$, $z_{2\ opt} = 0.93$, $z_{3\ opt} = 0.00$							
System cost (10^6): $f_{opt}^{\pm} = [1688.69, 2849.41]$							

$z_{2\,opt}$ = 1.00, and $z_{3\,opt}$ = 1.00 would be generated for the three regions when $q = [0.009, 0.011]$, and the related allowable diversion amounts would be 2.90×10^6 m^3, 5.70×10^6 m^3, and 3.50×10^6 m^3; nevertheless, when $q = [0.04, 0.06]$ and $[0.09, 0.11]$, 2.90×10^6 m^3, 5.60×10^6 m^3, and 2.50×10^6 m^3 of the allowable amount of the diversion will result for Regions 1 to 3.

The result of $T_{11}^{\pm} = T_{12}^{\pm} = T_{13}^{\pm} = T_{14}^{\pm} = T_{15}^{\pm} = 0$ indicates that there will be no incremental amount of floodwater being diverted under very-low to medium-high levels of flood flow when $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$. However, under a high flood flow level, the incremental amounts of the diverted floodwater for Region 1 would be $[0, 6] \times 10^6$ m^3 and $[0, 5] \times 10^6$ m^3 when $q = [0.009, 0.011]$ and $[0.04, 0.06]$. Region 2 would have an incremental amount of floodwater of $[0, 8] \times 10^6$ m^3 when $q = [0.009, 0.011]$ and no incremental amount of floodwater would result when $q = [0.04, 0.06]$ and $[0.09, 0.11]$. Under a very-high level of the flood flow, Region 1 would have an incremental diversion amount of floodwater of $[5, 7] \times 10^6$ m^3 when $q = [0.009, 0.011]$, $[4, 6] \times 10^6$ m^3 when $q = [0.04, 0.06]$, and $[3, 5] \times 10^6$ m^3 when $q = [0.09, 0.11]$; and an incremental amount of floodwater of $[5.5, 8] \times 10^6$ m^3 when $q = [0.009, 0.011]$, and $[4.5, 7] \times 10^6$ m^3 when $q = [0.04, 0.06]$ and $[0.09, 0.11]$. The incremental amount of diverted floodwater would be zero for Region 3 under any of the flood flow levels because Region 3 is banned from expanding its capacity.

In regard to excess amounts within the diversion, $S_{11}^{\pm} = S_{12}^{\pm} = S_{13}^{\pm} = S_{14}^{\pm} = 0$ shows that when $\theta = \left[[0.09, 0.11],\ [0.19, 0.21]\right]$ and $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$, the amount of excess diverted floodwater would be zero for all three regions under very-low to medium flood flow levels, with a probability of occurrence between 5% and 40%. However, under medium-high to very-high flood flow levels, excess diversion amounts will result for the three regions and such amounts would vary according to different risk levels (q) of violating the expansion constraint and the safety coefficient (θ) associated with those excess amount of floodwater. For instance, when $\theta = [0.09, 021]$, only Region 1 has an excess amount of diverted floodwater when $q = [0.009, 0.011]$ during a medium-high flood flow level, and the associated amount is $[0, 011] \times 10^6$ m^3; in comparison with a situation where $\theta = [0.11, 019]$, the floodwater amount changes to $[0, 010] \times 10^6$ m^3. Under a high flood flow level, the excess diversion amount of floodwater for Region 1 are $[0.21, 0.61] \times 10^6$ m^3, $[0, 1.42] \times 10^6\ m^3$ and $[0, 1.59] \times 10^6$ m^3 when $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$, whereas diversion amounts of $[0.12, 0.60] \times 10^6$ m^3, $[0, 1.49] \times 10^6$ m^3 and $[0, 1.68] \times 10^6$ m^3 would result when $\theta = [0.11, 019]$. Nevertheless, excess amounts of floodwater of $[0, 0.11] \times 10^6$ m^3, $[0.04, 0.92] \times 10^6$ m^3 and $[0.37, 1.09] \times 10^6$ m^3 would be generated when $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$ under a very-high flood flow level, and such amounts would be $[0, 0.10] \times 10^6$ m^3, $[0.06, 0.99] \times 10^6$ m^3 and $[0.29, 1.18] \times 10^6$ m^3 when $\theta = [0.11, 019]$. For Region 2, the excess diverted amount of floodwater under a medium-high flood flow level would be $[0, 1.35] \times 10^6$ m^3, $[0, 2.57] \times 10^6$ m^3 and $[0, 3.00] \times 10^6$ m^3 when $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$. When the flood flow level is high, the excess amount would be $[1.34, 1.35] \times 10^6$ m^3, 2.57×10^6 m^3 and $[3.00, 3.32] \times 10^6$ m^3 when $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$. Under a very-high flood flow level, $[1.34, 1.35] \times 10^6$ m^3 of the excess diversion amount would result when $q = [0.009, 0.011]$. When $q = [0.04, 0.06]$ and $[0.09, 0.11]$, such excess diversion amount would be 2.57×10^6 m^3 and $[3.18, 3.32]\times10^6$ m^3. Although Region 3 should not be expanded and the incremental amount is zero, an excess diversion amount would still be generated under medium-high to very-high flood flow levels. For example, during a high flood flow level, the excess diversion amount for Region 3 would be $[0.89, 0.98]\times10^6$ m^3, $[0.43, 1.51]\times10^6$ m^3 and $[0, 1.59]\times10^6$ m^3 when $q = [0.009, 0.011]$, $[0.04, 0.06]$, and $[0.09, 0.11]$. In contrast, such amounts would change to $[0.46, 0.48]\times10^6$ m^3, $[0.48, 1.49]\times10^6$ m^3 and $[0, 1.56]\times10^6$ m^3 under a situation when $\theta = [0.11, 019]$.

The expected system cost also varies under different risk levels (q) and safety coefficient (θ) (Figures 3.11 and 3.12). Such variations can provide valuable information on decision makers' preference toward the trade-offs between system cost and risk of violating the constraint. For example, under a situation where the safety coefficient (θ) is set at $[0.09, 0.21]$ when the risk level (q) equals to $[0.009, 0.011]$, the resulted system cost would be $\$[2087.18, 3784.40]\times10^6$. However, as the risk level increases, the system cost would be $\$[1785.73, 3076.41]\times10^6$ and $\$[1688.85, 2848.61]\times10^6$ when $q = [0.04, 0.06]$ and $[0.09, 0.11]$. Therefore, it is observed that an increased risk level would lead to a decreased system cost. Similarly, if $\theta = [0.11, 019]$, the generated system cost would be $\$[2126.70, 3820.28]\times10^6$, $\$[1785.96, 3077.26]\times10^6$ and $\$[1688.69, 2849.41]\times10^6$ when $q = [0.009, 0.011]$, $[0.04, 0.06]$ and $[0.09, 0.11]$. Generally, a lower q level signifies that the chance of violating the constraint is lower, leading to a higher system cost. On the contrary, a higher q level means that the system

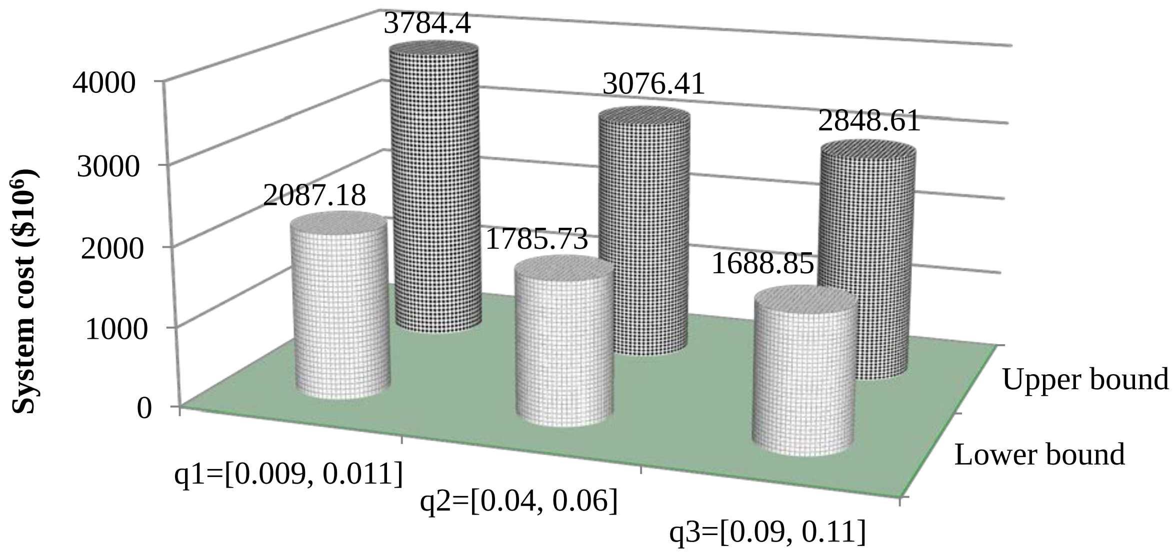

Figure 3.11 System cost under different q levels when $\theta = [0.09, 0.21]$

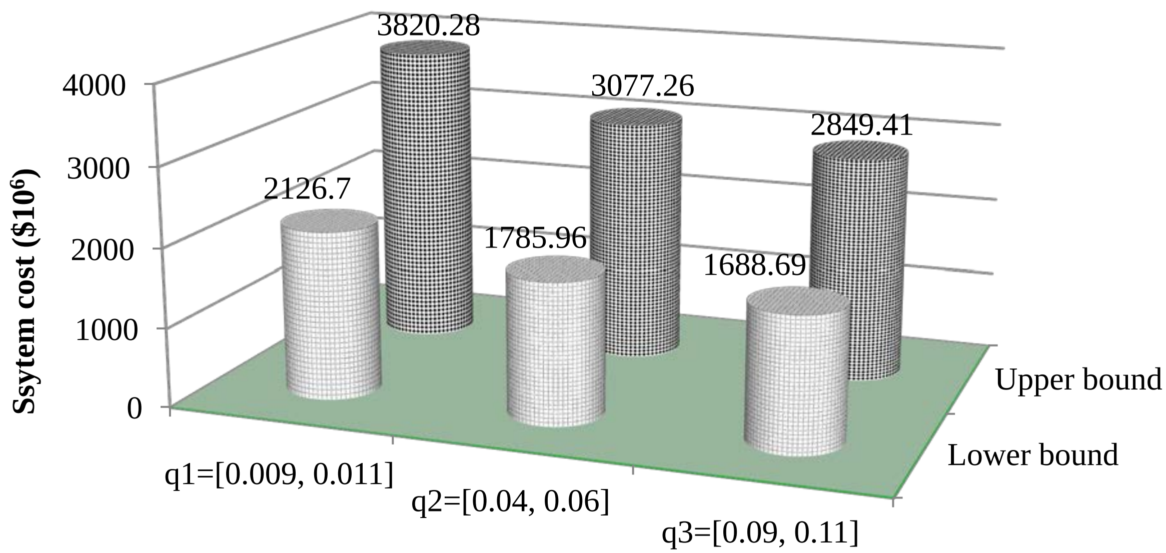

Figure 3.12 System cost under different q levels when $\theta = [0.11, 0.19]$

constraint can be allowed to be violated due to limited budget; thus, leading to a decreased system cost.

3.4 Discussion

Solutions generated from the DITMIC method can be used to provide reasonable results related to flood-diversion patterns and capacity-expansion schemes with a minimized system cost. The embedded complexity of the targeted system is primarily associated with the pre-regulated allowable diversion amount of floodwater (e.g., first-stage variable) before the occurrence of the random flood flow. In DITMIC, the expected system cost contains the following three parts: 1) regular cost for the diversion amount regarding the pre-regulated allowable diversion target, 2) penalty resulting from diverting the excess amount of floodwater, and 3) capital cost for the capacity-expansion for the three diversion regions. When the pre-regulated allowable diversion targets are set to have lower levels, penalties would have to be paid if such allowances are violated. Conversely, a higher level of the allowable diversion target would lead to a waste of the diversion capacity. Therefore, a lower level of the allowable diversion target is often associated with a situation where the local authority is optimistic about the future conditions. This will result in a higher risk of system failure due to higher excess floodwater and the related higher penalties. On the contrary, when the local authority is too conservative about the diversion in the future and assigns a higher level on the allowable diversion target, it will lead to lower excess floodwater and lower penalties, but a higher chance of wasting the resources (e.g., diversion capacity) (Wang and Huang, 2013b).

In the proposed DITMIC method, the allowable diversion amount ($W_i^{\pm}$) is considered as a decision variable (where $W_{i\,opt}^{\pm} = W_i^{-} - \Delta W_i\, z_i$ and $\Delta W_i = W_i^{+} - W_i^{-}$) in order to avoid any over- or under-estimation for the first-stage variables (Wang and Huang, 2013b). Moreover, multiple scenarios would result corresponding different policies on the flood-diversion management systems under multiple uncertainties. As a result, the proposed DITMIC method has the ability to provide more effective policy scenarios for the planning of flood-diversion management systems. On one hand, planning for a higher capacity-expansion level is associated with higher expansion cost. In this case, the incremental amount of floodwater is increased, resulting in a decrease for the excess flood-diversion amount. Consequently, higher expected system cost along with lower system-failure risk would be generated. On the other hand, willingness to accept a lower level of capacity-expansion would result in lower system cost; however, higher chance of violating the system constraints would result.

Generally, the proposed DITMIC method has the following advantages. Firstly, DITMIC can reflect system complexities and deal with multiple uncertainties expressed as intervals, dual intervals, and probability distributions. For example, it could handle uncertainties (expressed as conventional intervals and dual intervals) that exist in the constraint's left-hand-side. At the same time, multiple uncertainties are also presented on the constraint's right-hand-side as intervals and probability distributions. Secondly, DITMIC can be effective in analyzing the dynamic features of capacity-expansion planning when multiple regions, various flood flow levels, and different capacity-expansion options are involved. Thirdly, DITMIC has the ability to generate solution variables that are expressed in binary and continuous forms. Binary variables refer to the solutions for capacity-expansion schemes, whereas continuous variables indicate solutions for flood-diversion patterns. Fourthly, detailed information could be provided on policy analysis in relation to different levels of economic penalties when the pre-regulated targets are violated. Lastly, decision alternatives can be provided in order to select a desired flood-diversion plan based on decision makers' implicit knowledge and the future conditions regarding the objective and its related constraints.

3.5 Summary

In this study, a DITMIC method has been developed for the planning of flood-diversion management systems under multiple uncertainties. The DITMIC method integrates two-stage stochastic programming, mixed-integer linear programming, interval linear programming and chance-constrained programming into a general optimization framework. In addition, the proposed DITMIC method can handle uncertainties expressed as probability distributions and intervals. The pre-regulated flood-diversion policy can be integrated into the proposed method and the economic consequences of violating the policy can be also reflected. Moreover, a concept of dual interval has been introduced into the DITMIC method in order to reflect the system that is highly complex and uncertain. Furthermore, a concept of interval-valued probability is adopted in order to reflect the uncertain nature of the probability distribution.

The DITMIC method is capable of being divided into two scenarios with each having three probability levels of violating the system constraints which correspond to decision makers' implicit knowledge and attitude towards the objective-function value and the associated constraints. The proposed DITMIC method can also be used in analyzing various policy scenarios that are associated with different levels of economic penalties. The DITMIC is transformed into two submodels through an interactive algorithm. One of the submodels corresponds to the lower bound of the objective-function value, while the other corresponds to the upper bound of the objective-function value. Solutions for the flood-diversion patterns, capacity-expansion schemes, as well as the information on system-failure risk can be obtained. They are usually expressed as deterministic values and/or intervals.

The developed DITMIC method has been applied to a case study of flood management with regard to the planning of optimized flood-diversion patterns and capacity-expansion schemes. Reasonable solutions have been generated for both binary and continuous variables. Binary variables provide the desired capacity-expansion schemes while continuous ones offer flood-diversion patterns for the diversion regions. In addition, multiple decision alternatives have been generated, providing more decision alternatives on the selection of desired flood-diversion patterns and capacity-expansion schemes with minimized system cost. Therefore, decision makers can pick the best solution based on their implicit knowledge and the projected conditions in the future. The proposed DITMIC method can also be applied to the planning of other environmental management problems such as solid waste management, air pollution control planning, and energy systems optimization where the analysis of policy scenarios are required and the associated uncertainties are expressed in multiple forms.

CHAPTER 4

A FACTORIAL DUAL-INTERVAL PROGRAMMING APPROACH FOR PLANNING MUNICIPAL WASTE MANAGEMENT SYSTEMS

4.1 Background

Due to growing population and increasing concern over the environment, municipal solid waste should be properly treated and disposed through a number of options, such as landfilling, composting, incinerating and recycling (Huang and Chang, 2003; Thompson and Tanapat, 2005; Zeng and Trauth, 2005; Lu et al., 2009). In the planning of municipal solid waste management systems, extensive uncertainties such as waste generation rates, collection fees, transportation costs, and waste treatment costs may exist in many aspects of the system components (Liu et al., 2009). These complexities, as well as their associated uncertainties, may be further multiplied by not only the differences among implicit knowledge from the decision makers but also by the interactions of various uncertain system parameters. Therefore, it is optimal to develop an advanced inexact optimization method to support the management of municipal solid waste (MSW) under uncertainties.

During the past decades, a great number of inexact mathematical optimization methods were proposed for tackling uncertainties in solid waste management, and these methods can be grouped into stochastic mathematical programming, fuzzy mathematical programming, and interval mathematical programming (Huang et al., 1992, 1995; Chang and Wang, 1996, 1997; Chanas and Zielinski, 2000; Maqsood and Huang, 2003; Yeomans et al., 2003; Ekmekcioglu et al., 2010). Among them, the interval linear programming (ILP) method was generally adopted when the distributional information of the parameters was unknown. Nevertheless, in applications of the ILP method, difficulties may arise when it comes to information acquisition, where various data sources may lead to different ranges for each uncertain parameter. For example, the rate of waste generation for a given area may be uncertain due to the existence of multiple information sources and differences in statistical approaches. Each of the information sources and/or statistical methods may lead to a specified range for the rate, resulting in multiple intervals.

To account for such complexities, a dual-interval linear programming (DILP) approach was proposed by (Liu et al., 2009). In general, dual interval refers to a situation where the boundaries of an interval-valued number are not clearly stated. For instance, a single interval is usually presented as $[a, b]$ (a and b are deterministic values), whereas a dual interval is expressed as $\big[[a, c], [d, b]\big]$; thus, $[a, c]$ and $[d, b]$ can be regarded as interval-valued boundaries of the lower bound and upper bound of the single interval, and they represent imprecise information (Liu and Huang, 2009; Liu et al., 2009). Compared to existing ILP methods, the DILP approach is more effective in tackling the problem when highly uncertain information is presented (e.g., parameters that are without distributional information and are based on the opinions from various sources) (Liu and Huang, 2009; Liu et al., 2009). Although the DILP method can deal with uncertainties expressed as single intervals and dual intervals, it lacks the ability to analyze the individual effects of the uncertain inputs, as well as their interactive effects on the modeling outputs.

Factorial analysis was extensively used to discover the individual effects of the input parameters and their interactions on a system response (Box et al., 1978; Jaccard, 1998;

Kalil et al., 2000; Viviani et al., 2000; Montegomery, 2001; Hambli, 2002; Park and Ahn, 2004; Rekow et al., 2006; Wahdame et al., 2009; Zhou and Huang, 2011; Wang and Huang, 2013a). For example, Loh et al. (1989) conducted a 3^4 factorial design on a vertical machining centre to find out the effects of ball-burnishing parameters on the surface roughness of certain specimens. Qin et al. (2008) incorporated a 2^4 factorial design into a stochastic model system in order to analyze the effects of inherent uncertainties in hydrocarbon-contaminant transport processes within the subsurface. In the research conducted by Onsekizoglu et al. (2010), a 2^3 factorial design was carried out in order to investigate the influence of $CaCl_2$ concentration, flow rate, and temperature. Zhou and Huang (2011) proposed a factorial two-stage stochastic programming approach and applied it to water resources management. In this research, a 2^{9-3} fractional factorial design was conducted to identify the individual and combined effects of 9 uncertain parameters on the net system benefit. Fu et al. (2013) incorporated factorial analysis into the optimization of reservoir operation management (ROM) under multiple uncertainties, in which significant factors as well as their interaction were analyzed to identify the optimal parameter inputs, in order to achieve maximized system benefits. Wang and Huang (2014) adopted Taguchi's orthogonal arrays design within mixed-level factorial experiment for decision-making in water resources management. In this study, the Taguchi's orthogonal array design was firstly performed to identify significant factors that affected the system's total net benefit. Then, a mixed-level factorial experiment was used to reveal the interactions among those important factors that were associated with different levels. However, previous studies mainly focused on the effects of simple intervals. When the available information can merely be expressed as dual intervals, more advanced approaches are then needed to tackle the relevant complexities in the effects from such uncertain parameters and their interactions.

Therefore, as an extension of previous works, this research aims to develop a factorial dual-interval programming (FDIP) method to support municipal solid waste management under uncertainty. The proposed approach will be the first attempt to integrate multivariate factorial analysis and dual-interval linear programming into a general framework. Through factorial analysis, individual and interactive effects of the uncertain parameters (presented as single intervals or dual intervals) will be analyzed for the lower bound and upper bound of the system output under various scenarios. The developed approach will then be applied to a case study of municipal solid waste management to demonstrate its applicability.

4.2 Methodology

4.2.1 Dual-interval linear programming

According to Liu et al. (2009), a DILP model can be formulated as follows:

$$\text{Min } f^{\pm} = \left[C^{\pm}\right]^{\pm} X^{\pm} \tag{4.1a}$$

subject to:

$$\left[A^{\pm}\right]^{\pm} X^{\pm} \leq \left[B^{\pm}\right]^{\pm}, \tag{4.1b}$$

$$X^{\pm} \geq 0, \tag{4.1c}$$

where $\left[A^{\pm}\right]^{\pm} \in \left\{R^{\pm}\right\}^{m \times n}$, $\left[B^{\pm}\right]^{\pm} \in \left\{R^{\pm}\right\}^{m \times 1}$, and $\left[C^{\pm}\right]^{\pm} \in \left\{R^{\pm}\right\}^{1 \times n}$, $R^{\pm}$ represents a set of interval-boundary intervals (dual intervals).

Three assumptions are predefined in order to solve the dual-interval programming problem: (i) the lower and upper interval-valued bounds have no overlap, (ii) the dual interval has no distributional information, and (iii) the interval-valued boundaries are independent (Liu et al., 2009). Thus, equivalence class of random intervals can be firstly chosen according to the decision makers' implicit knowledge of the end points (Joslyn, 2003; Liu et al., 2009). Then, the DILP model can be further divided into several Interval Linear Programming (ILP) models by using different combinations of the random intervals as follows:

$$\text{Min } f^{\pm} = C^{\pm} X^{\pm} \tag{4.2a}$$

subject to:

$$A^{\pm} X^{\pm} \leq B^{\pm}, \tag{4.2b}$$

$$X^{\pm} \geq 0, \tag{4.2c}$$

where $A^{\pm} \in \{R^{\pm}\}^{m \times n}$, $B^{\pm} \in \{R^{\pm}\}^{m \times 1}$, $C^{\pm} \in \{R^{\pm}\}^{1 \times n}$, $X^{\pm} \in \{R^{\pm}\}^{n \times 1}$, and $R^{\pm}$ represents a set of interval numbers (Huang et al., 1992).

According to the two-step method proposed by (Huang et al., 1992, 1995), each of the ILP models can be further transformed into two submodels. In this two-step method, the first submodel (f^{-}), which corresponds to the objective function's lower bound, is formulated first. Based on the solutions of the first submodel, the second submodel, f^{+}, will then be conducted, where this submodel matches the objective function's upper bound. The detailed solution method will be presented as follows (assume $b_i^{\pm} \geq 0$, and $f^{\pm} \geq 0$) (Huang et al., 1995; Nie et al., 2008; Liu et al., 2009):

$$\text{Min } f^{-} = \sum_{j=1}^{k_1} c_j^{-} x_j^{-} + \sum_{j=k_1+1}^{n} c_j^{-} x_j^{+}, \tag{4.3a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{ij}|^{+} Sign(a_{ij}^{+}) x_j^{-} + \sum_{j=k_1+1}^{n} |a_{ij}|^{-} Sign(a_{ij}^{-}) x_j^{+} \leq b_i^{+}, \forall i, \tag{4.3b}$$

$$x_j^{\pm} \geq 0, \forall j, \tag{4.3c}$$

where $x_j^{\pm}$, $j = 1, 2, \ldots, k_1$, represent interval variables in the objective function, and those interval variables have positive coefficients; $x_j^{\pm}$, $j = k_1+1, k_1+2, \ldots, n$, denote the interval variables that have negative coefficients. Therefore, by solving submodel (4.3), the associated solutions (e.g., $x^{-}_{j\,opt}$ ($j = 1, 2, \ldots, k_1$) and $x^{+}_{j\,opt}$ ($j = k_1+1, k_1+2, \ldots, n$)) can be obtained. Then, the upper bound of the objective function, f^{+}, can be developed as follows (assume $b_i^{\pm} \geq 0$, and $f^{\pm} \geq 0$) (Huang et al., 1995; Nie et al., 2008; Liu et al., 2009):

$$\text{Min } f^{+} = \sum_{j=1}^{k_1} c_j^{+} x_j^{+} + \sum_{j=k_1+1}^{n} c_j^{+} x_j^{-}, \tag{4.4a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{ij}|^{-} Sign(a_{ij}^{-}) x_j^{+} + \sum_{j=k_1+1}^{n} |a_{ij}|^{+} Sign(a_{ij}^{+}) x_j^{-} \leq b_i^{-}, \forall i, \tag{4.4b}$$

$$x_j^{\pm} \geq 0, \forall j, \tag{4.4c}$$

$$x_j^{+} \geq x^{-}_{j\,opt}, j = 1, 2, \ldots, k_1, \tag{4.4d}$$

$$x_j^{-} \leq x^{+}_{j\,opt}, j = k_1+1, k_1+2, \ldots, n, \tag{4.4e}$$

Solutions of $x^{+}_{j\,opt}$ ($j = 1, 2, \ldots, k_1$) and $x^{-}_{j\,opt}$ ($j = k_1+1, k_1+2, \ldots, n$) can be obtained through solving submodel (4.4). Therefore, solutions of model (3.2) are

$f^{\pm}_{opt} = \left[f^{-}_{opt}, f^{+}_{opt} \right]$ and $x^{\pm}_{j\,opt} = \left[x^{-}_{j\,opt}, x^{+}_{j\,opt} \right]$ (Huang et al., 1995; Nie et al., 2008; Liu et al., 2009).

The DILP model is capable of handling uncertainties presented as dual intervals in the system constraints' left- and right-hand sides. However, parameters under various given conditions will have different influences on the system output. Any changes of those parameters will result in significant influences on the model's performance. Therefore, in order to fully understand the system, it is important to investigate individual and interactive effects of the parameters in regard to their uncertain characteristics, and to eventually identify significant factors, as well as their joint-effects on the system output under various scenarios.

4.2.2 Factorial analysis

The idea behind factorial analysis is to arrange the responses in such a way that the variations in modeling responses are obtained under different combinations (Box et al., 1978; Qin et al., 2008; Zhou and Huang, 2011). In fact, among various kinds of general factorial design, the most important is the 2^k factorial design (Montegomery, 2001). A 2^k factorial design involves k factors and each factor is at two levels; thus, such a factorial design will require 2^k runs in total (Montegomery, 2001; Wang and Huang, 2013a). As indicated by the name, a 2^k factorial design requires $2 \times 2 \times \cdots \times 2 = 2^k$ runs and has advantages that all kinds of main effects and interactions can be considered (Montegomery, 2001; Park and Ahn, 2004).

In a 2^k factorial analysis, the treatment combinations can be expressed using standard order or Yates' order; factors are introduced one after another and each new factor is combined with those that are ahead of it (Box et al., 1978; Zhou and Huang, 2011; Wang and Huang, 2013a). For example, a 2^4 factorial design involves four factors, namely *A*, *B*, *C* and *D*; the standard order for such a design is presented as (1), *a*, *b*, *ab*, *c*, *ac*, *bc*, *abc*, *d*, *ad*, *bd*, *abd*, *cd*, *acd*, *bcd*, and *abcd*. In this case, (1) signifies that all of the four factors are at their low levels; *ab* means that factors *A* and *B* are at their high levels while factors *C* and *D* are at their low levels. Moreover, *abc* denotes that factors *A*, *B* and *C* are at their high levels and factor *D* is at its low level (Box et al., 1978; Montegomery and Runger, 2011; Zhou and Huang, 2011; Wang and Huang, 2013a).

However, within such a 2^k factorial design, the increased number of factors will cause the runs of performing a complete factorial design to be augmented; thus, resulting in high volume of computational runs (Dasgupta et al., 1998; Montegomery, 2001; Park and Ahn, 2004; Zhou and Huang, 2011; Wang and Huang, 2013a). For instance, a full 2^7 factorial design has 7 factors and each of the factors is at two levels; thus, the number of runs involved in such design would be 128 in total; moreover, there are 127 degrees of freedom in this factorial design. In this design, only 7 runs correspond to main effects, 21 runs are associated with two-factor interactions, and the remainder (e.g., 99 degrees of freedom) correspond to higher interactions (e.g., three-factor interactions) (Montegomery, 2001; Zhou and Huang, 2011). Since most systems are led by main effects as well as their low-order interactions, the desired information could be achieved through running a portion of the complete set of runs of the factorial design (Montegomery, 2001; Zhou and Huang, 2011; Wang and Huang, 2013a). A fractional factorial design is a variation of the basic factorial design in which only a portion of the runs are performed (Montegomery, 2001). A 2^{k-p} fractional factorial design symbolizes that in a 2^k fractional factorial design, the number of runs performed is 2^{k-p} and it is usually designed to be able to consider main effects and two-way interactions (Park and Ahn, 2004). In a 2^{k-p} fractional factorial design, p independent generators are selected so as to get the best possible alias relationships. Additionally, in order to obtain the alias structure, each effect is multiplied by the defining relation which consists of the p generators and their 2^p-p-1 interactions (Box et al., 1978; Montegomery, 2001). For example, a fractional factorial design with three factors (A, B, and C) can be regarded as a 2^{3-1} fractional factorial design. Within such a design, C=AB and I=ABC are chosen as the design generator and defining relation. As a result, through multiplying the effects (e.g., A, B, and C) by the defining relation (e.g., I=ABC), the alias can be achieved. For instance, the alias of A can be obtained by $A \times I = A \times ABC = A^2BC$. Since the square of any effect's sign is identity I, thus, A=BC. Similarly, the alias of B is B=AC, and the alias of C is C=AB(Montegomery, 2001). Moreover, such a 2^{3-1} fractional factorial design is called a Resolution III design since their main effects (e.g., main effect A) are aliased with two-factor interactions (e.g., joint effect BC). Designs of resolution for a factorial analysis can be categorized into three groups: Resolution III, Resolution IV, and Resolution V designs. They are vital in performing factorial design and their definitions are described as follows (Montegomery, 2001):

1) Resolution III designs: main effects are not aliased with other main effects, but they are aliased with two-factor joint effects; two-factor joint effects may be aliased with one another.

2) Resolution IV designs: main effects are not aliased with other main effects or with two-factor joint effects; however, two-factor joint effects are aliased with one another.

3) Resolution V designs: main effects or two-factor joint effects are aliased with other mains effects or two-factor joint effects, but two-factor joint effects are aliased with three-factor joint effects.

Since their main and low-order interaction effects are more significant, a 2^{k-p} fractional factorial analysis could be performed without losing important information. The following equations are used to assess the main and interactive effect (Montegomery, 2001; Zhou and Huang, 2011; Wang and Huang, 2013a):

$$E_i = \frac{2(\text{Contrast}_i)}{2^{k-p}} = \frac{\text{Contrast}_i}{2^{k-p-1}} \tag{4.5a}$$

and

$$SS_i = \frac{(\text{Contrast}_i)^2}{2^{k-p}} \tag{4.5b}$$

where E_i is the standardized effect of a factor or multifactor interaction. Contrast_i is calculated according to column I of the Yates' order table and SS_i is the sum of squares for factor i or multifactor interaction (Zhou and Huang, 2011; Wang and Huang, 2013a).

4.2.3 A factorial dual-interval programming approach

To tackle uncertainties expressed as single intervals and dual intervals, as well as to explore their main and interactive effects on the system output under different scenarios, factorial analysis can thus be integrated into the dual-interval programming framework. This leads to a factorial dual-interval programming (FDIP) model as follows:

$$\text{Min } f^{\pm} = \sum_{j=1}^{n} c_j^{\pm} x_j^{\pm} + \sum_{j=1}^{k} c_{1j}^{\pm} x_{1j}^{\pm} + \sum_{j=k+1}^{n} \ddot{c}_{2j}^{\pm} x_{1j}^{\pm} \tag{4.6a}$$

subject to:

$$\sum_{j=1}^{n} a_{rj}^{\pm} x_j^{\pm} \leq b_r^{\pm},\ r = 1, 2, \ldots, s \tag{4.6b}$$

$$\sum_{j=1}^{k} a_{1tj}^{\pm} x_{1j}^{\pm} + \sum_{j=k+1}^{n} \left(a_{2tj}^{\pm}\right)^{\pm} x_{1j}^{\pm} \leq \left(b_{1t}^{\pm}\right)^{\pm},\ t = 1, 2, \ldots, q \tag{4.6c}$$

$$\sum_{j=1}^{n} \ddot{a}_{vj}^{\pm} x_j^{\pm} \leq \ddot{b}_v^{\pm},\ v = s + 1, s + 2, \ldots, m \tag{4.6d}$$

$$\sum_{j=1}^{k} a_{1uj}^{\pm} x_{1j}^{\pm} + \sum_{j=k+1}^{n} \left(\ddot{a}_{2uj}^{\pm}\right)^{\pm} x_{1j}^{\pm} \leq \left(\ddot{b}_{1u}^{\pm}\right)^{\pm},\ u = q + 1, q + 2, \ldots, p \tag{4.6e}$$

$$x_j^{\pm} \geq 0,\ j = 1, 2, \ldots, n \tag{4.6f}$$

$$x_{1j}^{\pm} \geq 0,\ j = 1, 2, \ldots, n \tag{4.6g}$$

where $c_j^{\pm}$, $c_{1j}^{\pm}$, $a_{rj}^{\pm}$, $b_r^{\pm}$, $a_{1tj}^{\pm}$, and $a_{1uj}^{\pm}$ are interval parameters; $\left(a_{2tj}^{\pm}\right)^{\pm}$ and $\left(b_{1t}^{\pm}\right)^{\pm}$ are dual-interval parameters; $\ddot{c}_{2j}^{\pm}$, $\ddot{a}_{vj}^{\pm}$, $\ddot{b}_v^{\pm}$, $\left(\ddot{a}_{2uj}^{\pm}\right)^{\pm}$, and $\left(\ddot{b}_{1u}^{\pm}\right)^{\pm}$ are concerned modeling parameters expressed as single intervals and dual intervals. The lower bound and upper bound of the intervals correspond to the low level and high level in the factorial design, and both bounds of the intervals are with known values; r signifies the number of constraints within which the parameters are expressed as single intervals; t indicates the number of constraints within which the parameters are expressed as dual intervals; v and u entail the number of constraints involving concerned modeling parameters; m and p represent the total number of constraints (Wang and Huang, 2013a).

Model (4.6) can comprehensively reflect the uncertainties that exist in both decision variables and modeling parameters of the system. Firstly, uncertainties in decision variables can be solved by the two-step interactive algorithm proposed by (Huang et al., 1992). Secondly, the influential uncertain modeling parameters, as well as their interactive effects on the system output, can be reflected by performing factorial analysis. The detailed solution procedures for the FDIP method are as follows:

1. formulate the FDIP model;
2. select equivalence random intervals from the dual interval;
3. transform the FDIP model into several ILP models based on the above selected random intervals;
4. transform each ILP model into two submodels;
5. solve the two submodels for each of the ILP models and obtain solutions accordingly: $f_{opt}^{\pm} = \left[f_{opt}^{-},\ f_{opt}^{+} \right]$ and $x_{opt}^{\pm} = \left[x_{opt}^{-}, x_{opt}^{+} \right]$;
6. integrate the solutions;
7. choose one or more decision alternatives (e.g., one or more ILP models with different levels of the selected random intervals) and the associated uncertain parameter as the factor of interest for the factorial analysis;
8. conduct factorial analysis on the objective function value's lower bound and upper bound for each of the decision alternatives (e.g., each ILP models);
9. identify main effects and their interactions on the objective function value's lower bound and upper bound;
10. stop.

As a result, the solutions from the proposed FDIP method will not only provide conventional optimization results in terms of waste-flow allocation schemes and decision alternatives but also reveal detailed effects of the selected uncertain parameters and their interactions on the lower bound and upper bound of the system output.

4.3 Application to municipal solid waste management planning

4.3.1 Statement of problems

A case study for the planning of municipal solid waste (MSW) management systems is to be adopted for the proposed FDIP method (Liu et al., 2009). The study area includes the following three components: three municipalities, a waste-to-energy (WTE) facility and a landfill. In this case study, three periods are considered and each period has a time interval of five years. As illustrated in Figure 4.1, an existing landfill and a WTE facility are available to serve the municipal solid waste disposal needs over a planning horizon of about 15 years.

Waste generation rates of the three municipalities are presented in Table 4.1. It is indicated that waste generation rates vary among the three municipalities during three periods. This is because waste generation rates are affected by many factors such as population growth, economic development, and human activities (Liu et al., 2009). Table 4.2 shows the transportation costs and the related operational costs of the two facilities. It is usually difficult to estimate the specific costs and revenue for the system components (e.g., the WTE facility) due to variations in waste density, moisture content, temperature, and packing method. Thus, transportation costs, treatment costs, as well as disposal costs of the waste material would be uncertain and would vary temporally and spatially due to complexities in solid waste characteristics, socioeconomic conditions, and geographical conditions (Liu et al., 2009).

Table 4.3 represents the maximum capacities of the two facilities. Landfill capacity is interpreted as a single interval, whereas the capacity for the WTE facility is expressed as dual interval. Due to factors such as weight, compaction, and mass loss of the waste,

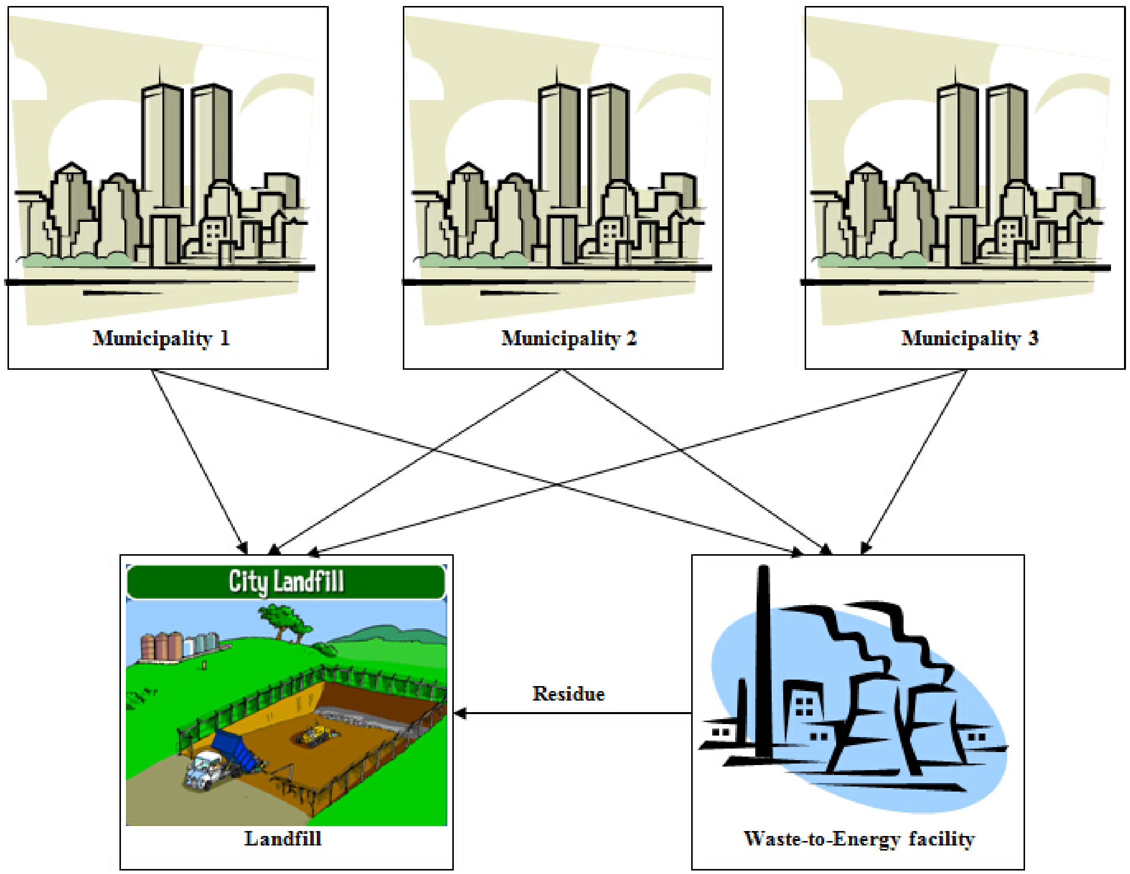

Figure 4.1 A study system of municipal solid waste management

Table 4.1 Waste generation rates

Waste generation rates (tonne/day)	Period		
	$k = 1$	$k = 2$	$k = 3$
Municipality 1	[200, 250]	[225, 275]	[250, 300]
Municipality 2	[350, 400]	[375, 425]	[400, 500]
Municipality 3	[275, 325]	[300, 350]	[325, 375]

Table 4.2 Transportation costs and operational costs

Data	Period		
	k = 1	k = 2	k = 3
Costs of transportation to landfill ($/tonne)			
Municipality 1	[12.1, 16.1]	[13.3, 17.7]	[14.6, 19.5]
Municipality 2	[10.5, 14.0]	[11.6, 15.4]	[12.8, 16.9]
Municipality 3	[12.7, 17.0]	[14.0, 18.7]	[15.4, 20.6]
Costs of transportation to Waste-to-Energy facility ($/tonne)			
Municipality 1	[9.6, 12.8]	[10.6, 14.1]	[11.7, 15.5]
Municipality 2	[10.1, 13.4]	[11.1, 14.7]	[12.2, 16.2]
Municipality 3	[8.8, 11.7]	[9.7, 12.8]	[10.6, 14.0]
Operational costs ($/tonne)			
Landfill	[30, 45]	[40, 60]	[50, 80]
Waste-to-Energy	[55, 75]	[60, 85]	[65, 95]

Table 4.3 Landfill and waste-to-energy capacities

	Capacity
Landfill (t)	$\left[5.18\times10^{6}, 5.23\times10^{6}\right]$
Waste-to-Energy (t/day)	$\left[[696, 704], [718, 726]\right]$

landfill capacity cannot always be a fixed (deterministic) value. Thus, estimations of the landfill capacity should be given as an interval value (Liu et al., 2009). The WTE facility also possesses similar characteristics except for the fact that it is more difficult to determine the lower bound and upper bound limits of the capacity, due to variations in working hours, the requirements for regular system maintenance, as well as the inconsistent manner among workers in operating the facility (Li et al., 2008). Therefore, dual intervals can be adopted as effective means to illustrate the capacity limits of the WTE facility (Liu et al., 2009).

The WTE facility generates an amount of residue, which is to be shipped directly to the landfill. While processing the waste in a WTE facility, a certain amount of revenue will be generated at around $15 to $25 per tonne of treated waste. Moreover, a safety coefficient is considered in this study due to the effects of traffic congestion and waste overloading at the WTE facility (Liu et al., 2009). The safety coefficient is also expressed as a dual interval: $\big[[0.09, 0.11], [0.19, 0.21]\big]$. Since the information on the end point of the dual interval is insufficient, the lower bound of the safety coefficient is between 0.09 and 0.11, and the upper bound is between 0.19 and 0.21. Then, according to the elicitation algorithm, [0.09, 0.21], and [0.11, 0.19] can be regarded as equivalent random intervals of the dual interval and each of the random intervals has a probability of 0.5 (Joslyn, 2003; Liu et al., 2009). Due to existence of uncertain parameters within the system (e.g., generation rates, transportation costs, treatment costs for the waste plus waste disposal costs), as well as the need to fully understand the individual and interactive effects of the uncertain parameters on the system output, the proposed FDIP method will be a benefit in dealing with such problems.

4.3.2 Modeling formulation

Due to uncertainties that exist in both decision variables and modeling parameters, the concern with such problems is how to effectively plan the waste-flow allocation patterns with a minimized overall system cost under several constraints, including landfill capacity, WTE facility capacity, and waste disposal demand constraints. The decision variables, $X_{ijk}^{\pm}$, represent the amount of waste allocated from municipality j to facility i during period k. The modeling parameters, such as $OP_{ik}^{\pm}$, $FE^{\pm}$, $RE_{k}^{\pm}$, $WG_{jk}^{\pm}$, $TL^{\pm}$, $[\theta^{\pm}]^{\pm}$, and $\left[TE^{\pm}\right]^{\pm}$, are chosen as the concerned factors for the factorial analysis. Therefore, we have:

$$\text{Min} f^{\pm} = 1825 \sum_{i=1}^{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \left[X_{ijk}^{\pm} \left(TR_{ijk}^{\pm} + OP_{ik}^{\pm}\right)\right]$$

$$+ \sum_{i=1}^{2} \sum_{k=1}^{3} \left[X_{2jk}^{\pm} \left(FE^{\pm} \left(FT_{k}^{\pm} + OP_{1k}^{\pm}\right) - RE_{k}^{\pm}\right)\right] \tag{4.7a}$$

subject to:

$$1825 \left[\sum_{i=1}^{2} \sum_{k=1}^{3} X_{1jk}^{\pm} + \sum_{i=1}^{2} \sum_{k=1}^{3} \left(X_{2jk}^{\pm}\right) FE^{\pm}\right] \leq TL^{\pm} \tag{4.7b}$$

[Landfill capacity constraint]

$$\sum_{j=1}^{3} X_{2jk}^{\pm} \left(1+\left[\theta^{\pm}\right]^{\pm}\right) \leq \left[TE^{\pm}\right]^{\pm}, \forall k \tag{4.7c}$$

[WTE capacity constraints]

$$\sum_{i=1}^{2} X_{ijk}^{\pm} \geq WG_{jk}^{\pm}, \forall j, k \tag{4.7d}$$

[Waste disposal demand constraints]

$X_{ijk}^{\pm} \geq 0, \forall i, j, k$ (4.7e)

[Non-negativity constraints]

where:

i = waste treatment/disposal facility, i = 1 for landfill and i = 2 for WTE;

j = municipality, j = 1 for municipality 1, j = 2 for municipality 2 and j = 3 for municipality 3;

k = time period, k = 1 for period 1, k = 2 for period 2 and k = 3 for period 3;

$X_{ijk}^{\pm}$ = waste flow from municipality j to facility i during time period k (tonne/day);

$TR_{ijk}^{\pm}$ = transportation costs from municipality j to facility i during time period k ($/tonne);

$OP_{ik}^{\pm}$ = operation costs of facility i during time period k ($/tonne);

$FE^{\pm}$ = residue flow rate from the WTE facility to landfill (% of incoming mass to the Waste-to-Energy facility);

FT_k = transportation costs of flow from the Waste-to-Energy facility to the landfill facility during time period k ($/tonne);

$RE_{\mathrm{k}}^{\pm}$ = revenue from the WTE facility during time period k ($/tonne);

$TL^{\pm}$ = capacity of the landfill facility (tonne);

$[TE^{\pm}]^{\pm}$ = maximum treatment capacity of the WTE facility (tonne/day);

$WG_{jk}^{\pm}$ = waste generation rate in municipality j during time period k (tonne/day).

4.3.3 Result analysis

Based on the proposed FDIP method, two major scenarios, each having three sub-scenarios, are studied. Thus, scenario 1 is assigned with a safety coefficient of

[0.09, 0.21]; scenario 2 is assigned with a safety coefficient of [0.11, 0.19], where each scenario has a probability of occurrence of 0.5. Under each of the above major scenarios, WTE capacities of [696, 718], [704, 718], and [704, 726] tonne/day are considered, with each having a probability of 0.33 (Joslyn, 2003; Liu et al., 2009). Table 4.4 shows the general solutions resulting from the FDIP method. It is shown that single interval and dual interval have been accounted to the results. For example, the amount of waste from municipality 3 to the landfill during the first period is $\left[275, [297.47, 313.86]\right]$ tonne/day and the associated system cost is $\$\left[262.097, [502.954, 502.975]\times10^6\right]$. Thus, dual interval has been well exhibited in the proposed FDIP method. It is also indicated that the waste from municipalities 1 and 3 during the entire planning horizon will be shipped to either the landfill or the WTE facility, whereas all of the waste from municipality 2 will be directly allocated to the landfill.

During the first period of the planning horizon, the amount of waste from municipality 1, 2, and 3 to the landfill would be $[200, 250]$, $[350, 400]$ and $\left[275, [297.47, 313.86]\right]$ tonne/day; only $\left[0, [11.14, 27.53]\right]$ tonne/day of the waste from municipality 3 would be transported to the WTE facility. This indicates that, in normal situations during the first planning period, [0, 11.14] tonne/day of the waste generated from municipality 3 will be shipped to the landfill. However, when traffic congestion or high volumes of waste generated from the municipality occur, [0, 27.53] tonne/day of the waste would be transported to the WTE facility. During the second period, municipality 1, 2, and 3 would transport all of the waste to the landfill. During the third period, municipality 1, 2, and 3 would deliver $[0, 50]$, $[400, 500]$, and $\left[0, [33.40, 49.79]\right]$

Table 4.4 Optimized waste-flow allocation of the FDIP method

Waste flow (t/day)	Facility i (i = 1, 2)	Municipality j (j = 1, 2, 3)	Period k (k = 1, 2, 3)	Optimized waste-flow allocation under $\theta = \left[[0.09, 0.11], [0.19, 0.21]\right]$ and $TE = \left[[696, 704], [718, 726]\right]$
$x_{111}^{\pm}$	1	1	1	[200, 250]
$x_{112}^{\pm}$	1	1	2	[225, 275]
$x_{113}^{\pm}$	1	1	3	[0, 50]
$x_{121}^{\pm}$	1	2	1	[350, 400]
$x_{122}^{\pm}$	1	2	2	[375, 425]
$x_{123}^{\pm}$	1	2	3	[400, 500]
$x_{131}^{\pm}$	1	3	1	[275, [297.47, 313.86]]
$x_{132}^{\pm}$	1	3	2	[300, 350]
$x_{133}^{\pm}$	1	3	3	[0, [33.40, 49.79]]
$x_{211}^{\pm}$	2	1	1	0
$x_{212}^{\pm}$	2	1	2	0
$x_{213}^{\pm}$	2	1	3	250
$x_{221}^{\pm}$	2	2	1	0
$x_{222}^{\pm}$	2	2	2	0
$x_{223}^{\pm}$	2	2	3	0

Table 4.4 (Cont.)

Waste flow (t/day)	Facility i (i = 1, 2)	Municipality j (j = 1, 2, 3)	Period k (k = 1, 2, 3)	Optimized waste-flow allocation under $\theta = [[0.09, 0.11], [0.19, 0.21]]$ and $TE = [[696, 704], [718, 726]]$
$x_{231}^{\pm}$	2	3	1	[0, [11.14, 27.53]]
$x_{232}^{\pm}$	2	3	2	0
$x_{233}^{\pm}$	2	3	3	[325, [325.21, 341.60]]
$f^{\pm}\ (10^6)$				[262.097,[502.954, 502.975]

tonne/day of the waste to the landfill, while 250 tonne/day of the waste from municipality 1 and $[325, [325.21, 341.60]]$ tonne/day of the waste from municipality 3 would be delivered to the WTE facility due to the gradually minimized working capacity of landfill and close proximity to the WTE facility of municipality 3. It is obvious from the results that the amount of waste-flow allocation from municipality 3 to both the landfill and the WTE facility is most vulnerable to changes in safety coefficient (e.g., θ) and the capacity of the WTE facility (e.g., *TE*).

The overall system cost throughout the planning horizon varies according to different scenarios resulting from dual uncertainties that exist in the safety coefficient and the WTE capacity. When decision makers put more emphasis on minimizing system cost, the resulting overall system cost of $\$[262.097, 502.954]\times10^6$ would be desirable. However, this would lead to the system unreliability when traffic congestion or high volumes of the waste generation occur. Thus, the system cost of $\$[262.097, 502.975]\times10^6$ would be a better choice to maintain system reliability in this scenario. Consequently, dual uncertain characteristics in the input parameters would result in dual uncertainties in the system output and multiple decision alternatives would be generated to provide different ranges of waste-flow allocation schemes and the associated system cost.

In fact, the proposed FDIP method can be regarded as an efficient approach to observe significant uncertain parameters as well as their joint effects on the lower bound and upper bound of the system cost under different scenarios. In model (4.7), twenty factors related to waste generation rates from three municipalities, operational costs and maximum capacities of the landfill and the WTE facilities, the ratio of residue generated from the WTE facility, and the safety coefficient of the WTE facility were selected for examination. Those factors include $WG_{a1}^{\pm}$, $WG_{b1}^{\pm}$, $WG_{c1}^{\pm}$, $WG_{a2}^{\pm}$, $WG_{b2}^{\pm}$, $WG_{c2}^{\pm}$, $WG_{a3}^{\pm}$, $WG_{b3}^{\pm}$, $WG_{c3}^{\pm}$, $OP_{l1}^{\pm}$, $OP_{w1}^{\pm}$, $OP_{l2}^{\pm}$, $OP_{w2}^{\pm}$, $OP_{l3}^{\pm}$, $OP_{w3}^{\pm}$, $FE^{\pm}$, $\theta^{\pm}$, $RE^{\pm}$, $TL^{\pm}$, and $TE^{\pm}$; they are symbolized as *A*, *B*, *C*, *D*, *E*, *F*, *G*, *H*, *J*, *K*, *L*, *M*, *N*, *O*, *P*, *Q*, *R*, *S*, *T*, and *U*. According to the proposed approach, a $2_{\mathrm{V}}^{20\text{-}11}$ fractional factorial design of resolution V was undertaken. Therefore, 512 runs are performed to conduct the factorial analysis of the objective function under different scenarios. Such a design can reveal information on the significant factors and their joint effects by running only a fraction of the total runs without losing significant information.

Through performing the $2_{\mathrm{V}}^{20\text{-}11}$ fractional factorial design, the influential factors that have apparent effects on the lower bound and upper bound of the system cost are identified as *A*, *B*, *C*, *D*, *E*, *F*, *G*, *H*, *J*, *K*, *L*, *M*, *O*, *P*, *Q* and *S*. This is common for all of the sub-scenarios under scenarios 1 and 2. However, their standardized effects, sum of squares and percentage of contributions vary slightly according to different scenarios resulting from the FDIP method. These main factors, as well as their interactions, showed various levels of effects on the lower bound and upper bound of the system cost.

Figures 4.2 and 4.3 show the Pareto Charts of the effects on the lower bound and upper bound of the system cost under sub-scenario 1 of scenario 1. According to this figure, it shows that factor *L*, the operational cost of the WTE facility during the first period, is most influential to the lower bound and upper bound of the system cost. Moreover, factor *L* has a positive effect with a percentage contribution of 29.9764% to the lower bound of the system cost, whereas this percentage has decreased to 29.1279% to the upper bound of the system cost. Thus, it can be concluded that factor *L* has a

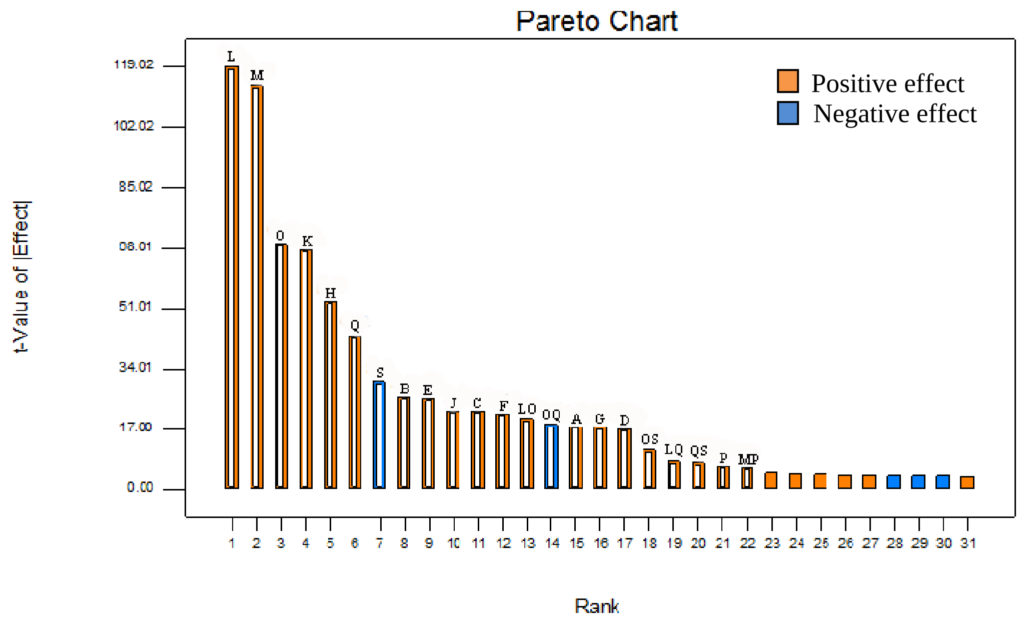

Figure 4.2 Pareto chart of the effects on lower bound of the system cost under sub-scenario 1 of scenario 1

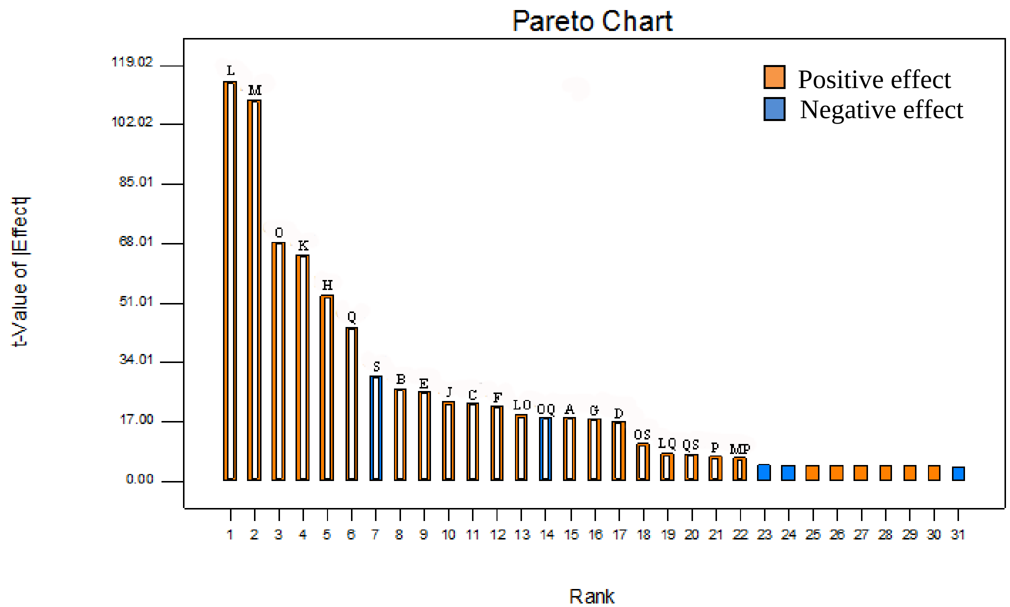

Figure 4.3 Pareto chart of the effects on upper bound of the system cost under sub-scenario 1 of scenario 1

slightly larger effect on the lower bound of the system cost than that on the upper bound of the system cost. Therefore, factor *L* has the largest effect on the whole system. Any variations in factor *L* will result in significant changes to the system performance due to increased operational costs of the WTE facility throughout the planning horizon. The factor that has the second largest effect on the system cost is *M* (operational costs of the landfill during the second period). Factor *M* also has a positive effect and contributes 27.4479% to the lower bound and 26.5449% to the upper bound of the system cost. Within all the main effects, *S* (revenue) is the only factor that has a negative effect on the system cost, which contributes 1.9380% to the lower bound and 2.0269% to the upper bound of the system cost. Other major factors contributed positively to the lower bound and upper bound of the system cost, respectively.

Figure 4.4 presents the identified six groups of two-factor interactions and their levels of contribution to the minimized system cost with regard to their lower bounds and upper bounds under all of the six sub-scenarios. For instance, each two-factor interaction has different levels of contribution to the lower bound and upper bound of the system cost under various sub-scenarios. Factor *LQ* contributes 0.1336% to the lower bound of the system cost under sub-scenario 1, whereas this percentage changes to 0.1322%, 0.1350%, 0.1332%, 0.1318%, and 0.1346% in sub-scenarios 2, 3, 4, 5, and 6. With regard to the upper bound of the system cost, *LQ* contributes 0.1382%, 0.1368%, 0.1397%, 0.1379%, 0.1364%, and 0.1393% under sub-scenarios 1, 2, 3, 4, 5, and 6.

Moreover, for each of the sub-scenarios presented in Figures 4.5 to 4.10, different two-factor interactions also possess varying levels of effects on the lower bound and upper bound of the system cost. For example, under sub-scenario 1, factor *OS* contributes

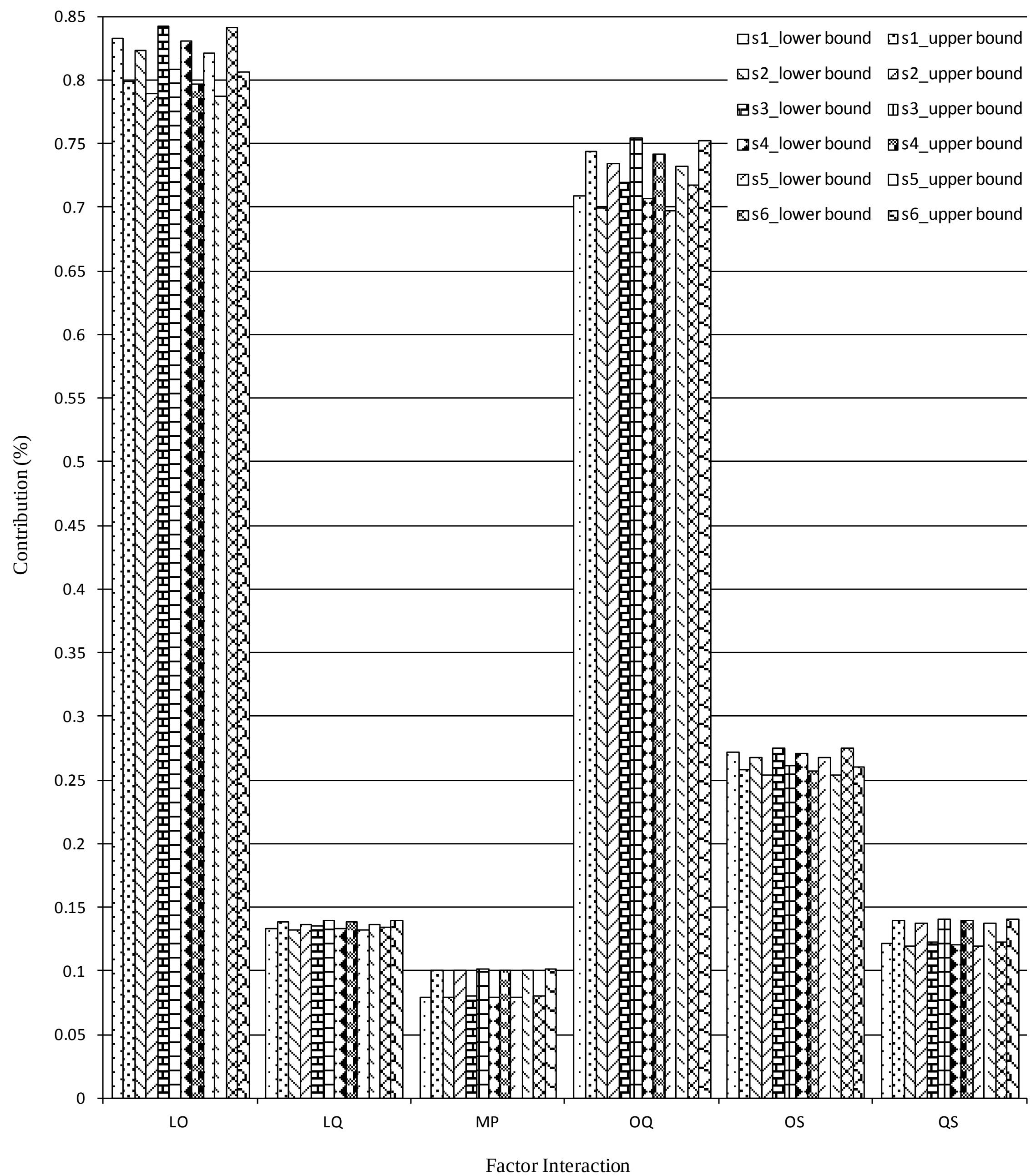

Figure 4.4 General outline of the interaction effects on the lower bound and upper bound of the system cost under different sub-scenarios

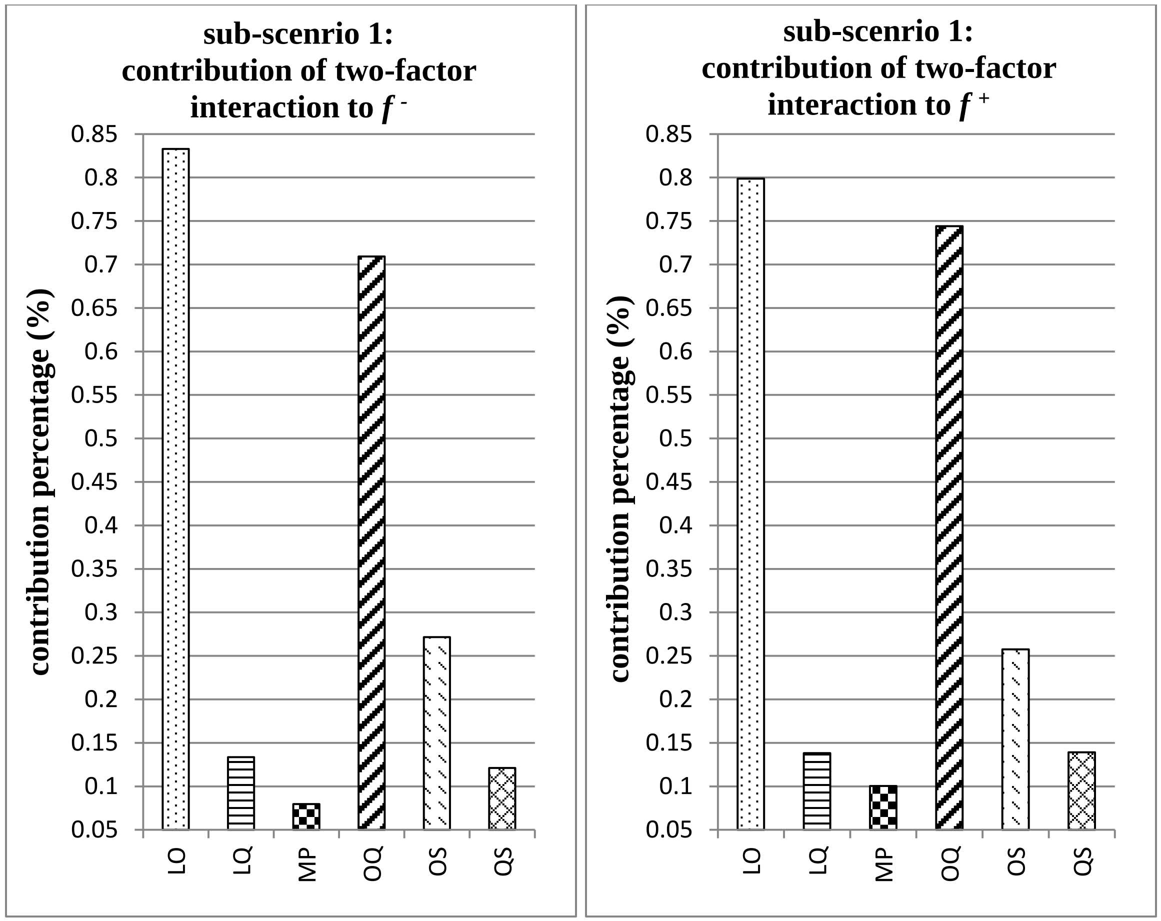

Figure 4.5 Factor interactions of LO, LQ, MP, OQ, OS, and QS to the lower bound and upper bound of system cost under sub-scenario 1

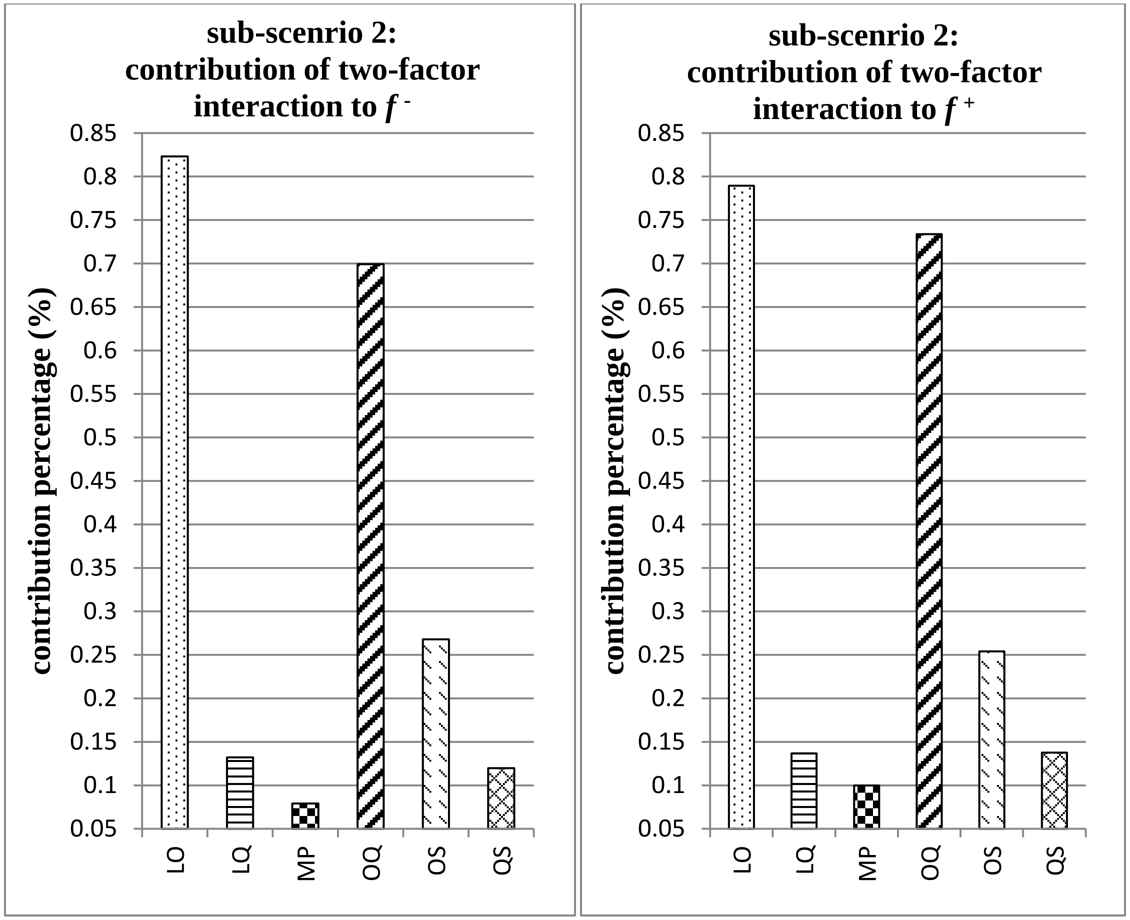

Figure 4.6 Factor interactions of LO, LQ, MP, OQ, OS, and QS to the lower bound and upper bound of system cost under sub-scenario 2

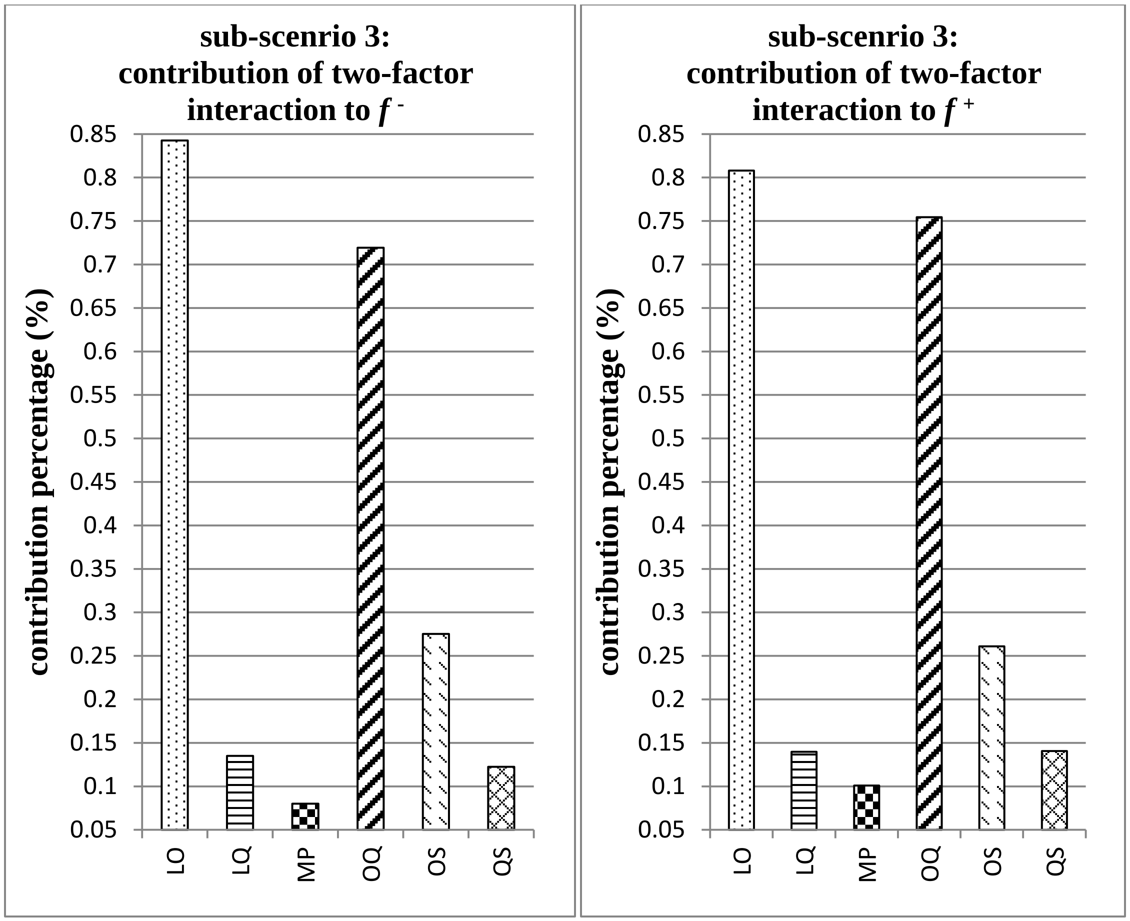

Figure 4.7 Factor interactions of LO, LQ, MP, OQ, OS, and QS to the lower bound and upper bound of system cost under sub-scenario 3

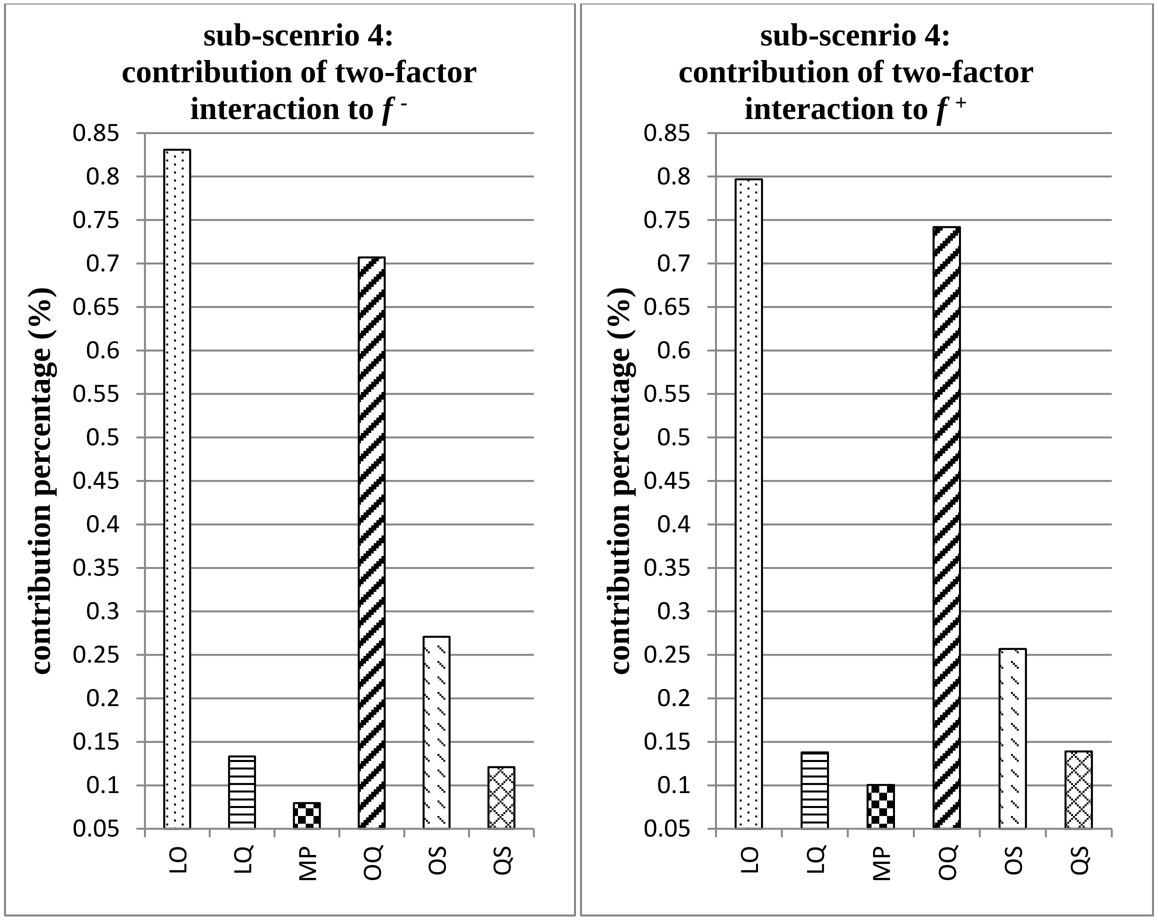

Figure 4.8 Factor interactions of LO, LQ, MP, OQ, OS, and QS to the lower bound and upper bound of system cost under sub-scenario 4

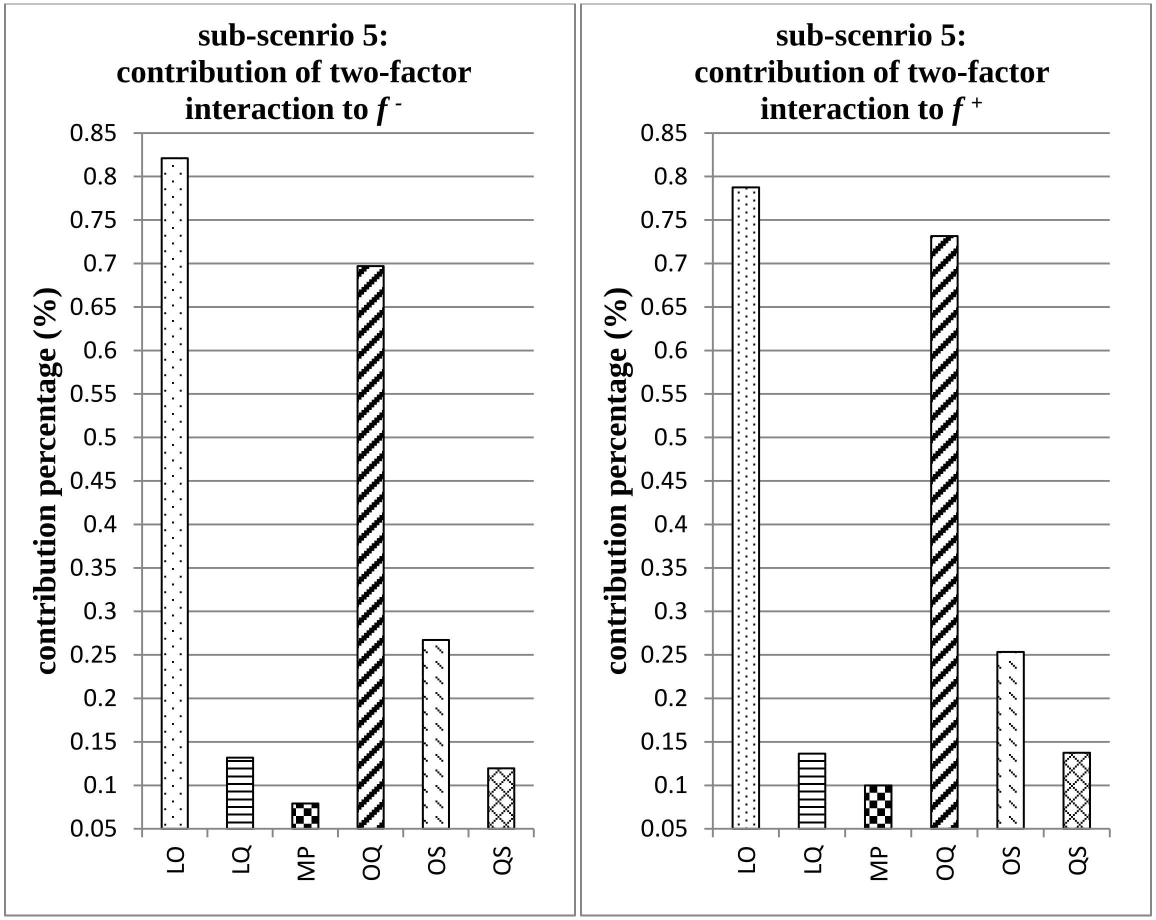

Figure 4.9 Factor interactions of LO, LQ, MP, OQ, OS, and QS to the lower bound and upper bound of system cost under sub-scenario 5

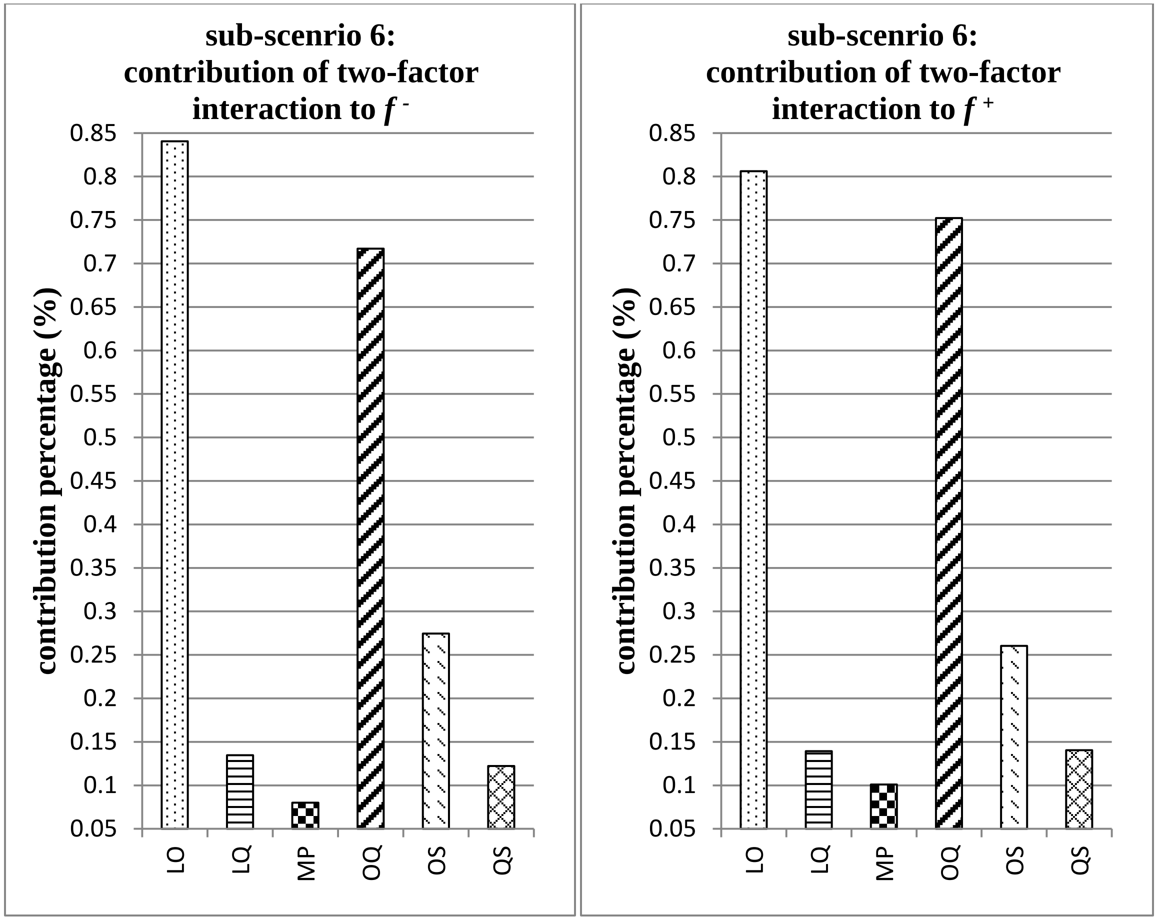

Figure 4.10 Factor interactions of LO, LQ, MP, OQ, OS, and QS to the lower bound and upper bound of system cost under sub-scenario 6

0.2716% to the lower bound of the system cost while factor *QS* contributes 0.1211%. Furthermore, the level of contribution level for factor *OS* decreases to 0.2575% for the upper bound of the system cost, whereas the contribution level of factor *QS* increases to 0.1391% for the upper bound of the system cost.

Figure 4.11 clearly illustrates the contribution percentage of *LQ* interactions (interactions of the operational costs for the WTE facility and the ratio of residue generated from the WTE facility during the first period) on the lower bound and upper bound of the system cost. It is obvious that the contribution percentage of *LQ* interactions varies for the lower bound and upper bound of the system cost. For instance, under sub-scenario 1 of scenario 1, the interaction of factor *LQ* contributes 0.1336% to the lower bound of the system cost; this percentage increases to 0.1382% for the upper bound of the system cost. Furthermore, the percentage contributions of *LQ* interactions are slightly different among sub-scenarios. For instance, *LQ* interactions have a percentage contribution of 0.1322% on the lower bound of the system cost under sub-scenario 2; this percentage then changes to 0.1350%, 0.1332%, 0.1318%, and 0.1346% for the lower bound of the system cost in sub-scenarios 3, 4, 5, and 6. Figure 4.12 shows the percentages of contribution of *QS* interactions (interactions of the ratio and revenue related to the WTE facility). For instance, the contribution percentages of *QS* for the lower bound of the objective function are 0.1211%, 0.1198%, 0.1224%, 0.1209%, 0.1195%, and 0.1222% for all the sub-scenarios. These percentages increases to 0.1391%, 0.1376%, 0.1406%, 0.1390%, 0.1374%, and 0.1404% for the upper bound of the objective function under all sub-scenarios. In contrast to the interaction effects of *LQ* and *QS*, the contribution levels of factor *OS* is slightly larger on the lower bound then that on

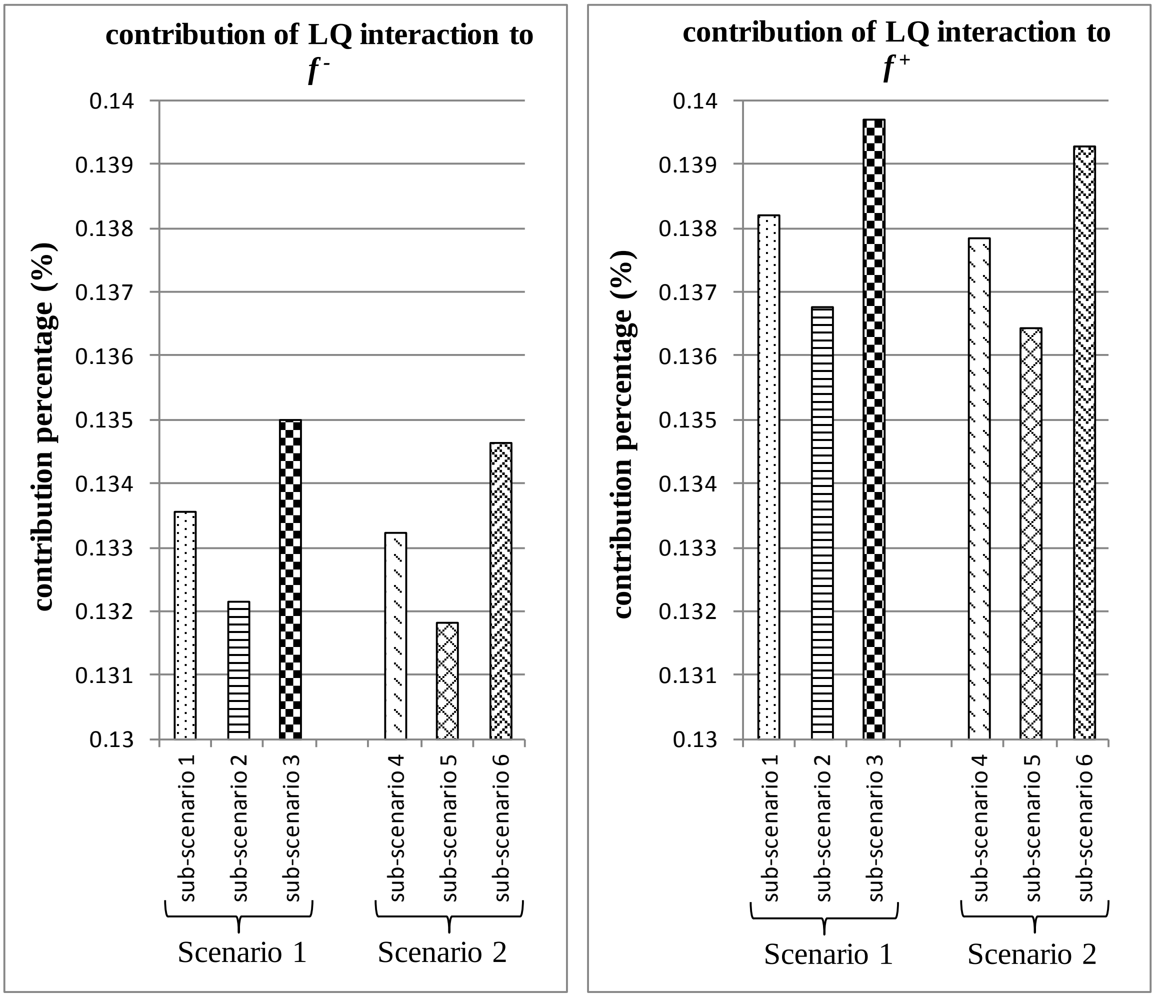

Figure 4.11 LQ interaction to the lower bound and upper bound of the system cost of different sub-scenarios under scenario 1 and scenario 2

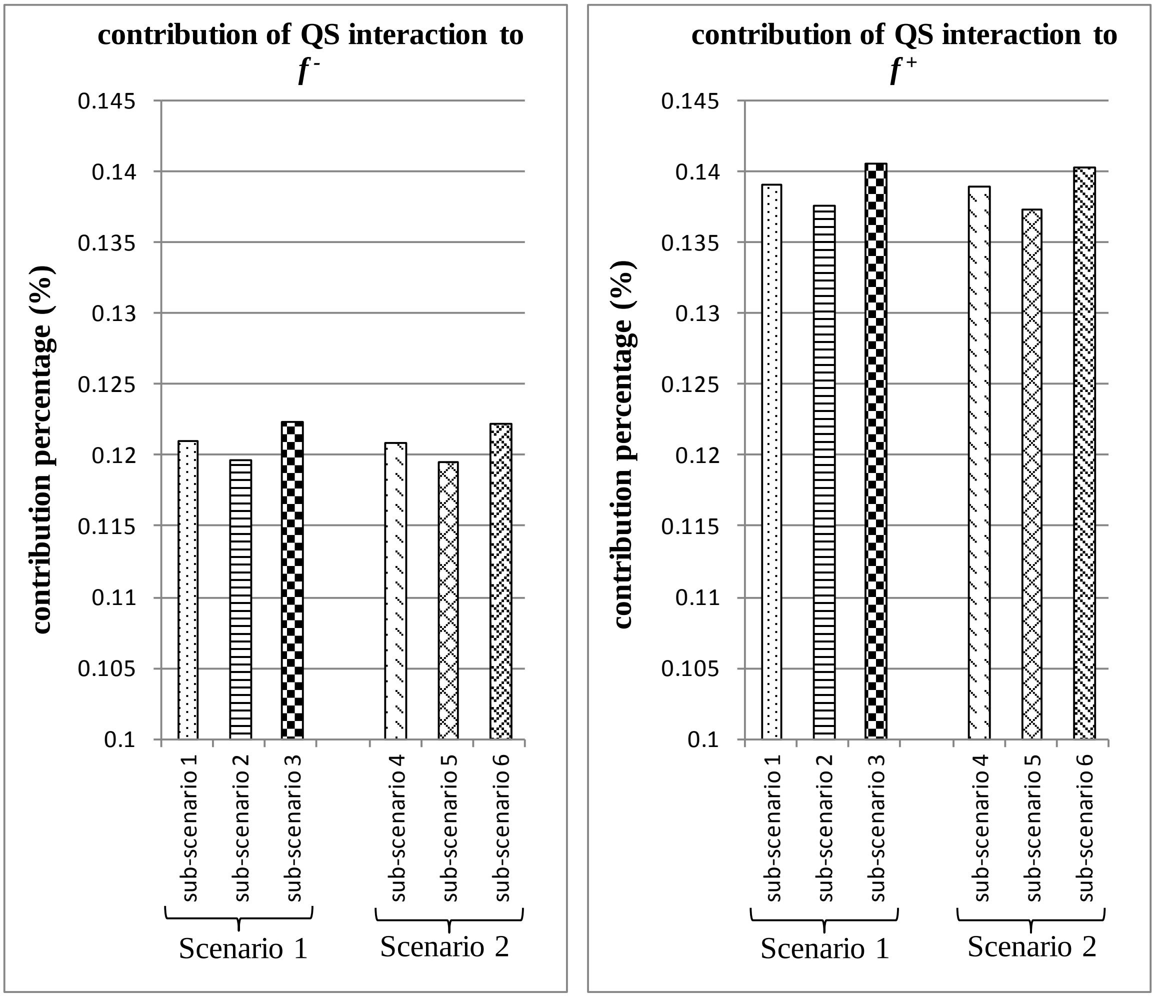

Figure 4.12 QS interaction to the lower bound and upper bound of the system cost of different sub-scenarios under scenario 1 and scenario 2

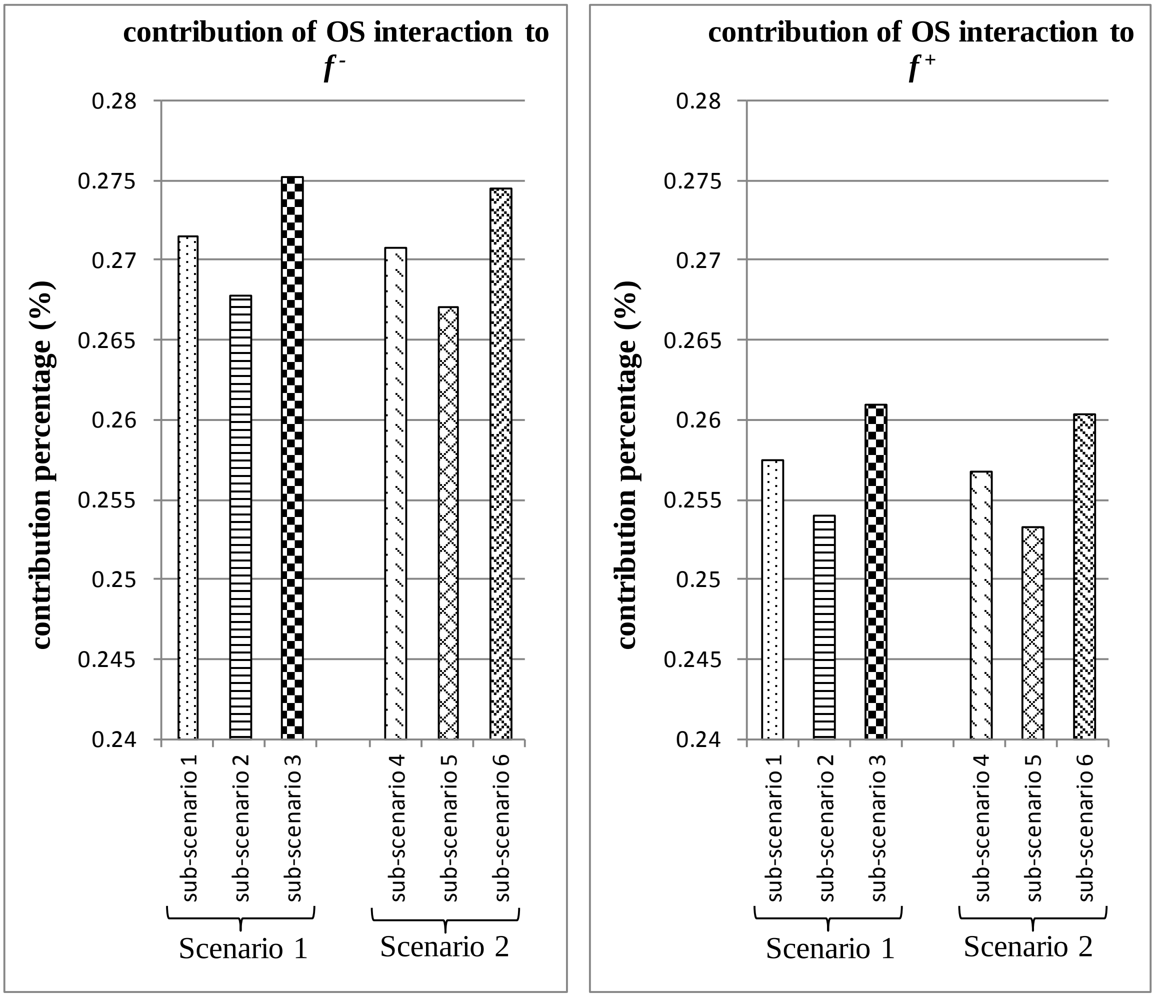

Figure 4.13 OS interactions to the lower bound and upper bound of the system cost of different sub-scenarios under scenario 1 and scenario 2

the upper bound of the minimized system cost. Figure 4.13 presents the contribution percentage of *OS* interactions on the system cost under various sub-scenarios. For instance, the contribution levels of OS interactions is 0.2753% for the lower bound of the system cost and 0.2610% for the upper bound of the system cost under sub-scenario 3 of scenario 1. These percentages then decrease to 0.2708% for the lower bound and 0.2568% for the upper bound of the system cost during sub-scenario 4 under scenario 2.

Figures 4.14 to 4.19 illustrate the interaction plots for *LQ* (opW1 and FE: operational costs of the WTE facility during the first period and the ratio of residue generated from the WTE facility), *QS* (FE and RE: the ratio of residue and the revenue generated from the WTE facility during the third period), and *OS* (opL3 and RE: operational costs of the landfill during the third period and the revenue generated from the WTE facility) on the lower bound and upper bound of the system cost in sub-scenario 1 under scenario 1, since other sub-scenarios delineate similar trends, but with different values of the interactive effects. For instance, Figure 4.14 shows that when the ratio of residue generated from the WTE facility is at its low level, a decrease from 75 to 55 \$/tonne in operational costs of the WTE facility during the first period would result in a decrease from 3.57×10^8\$ to 3.24×10^8\$ for the lower bound of the system cost. Therefore, the lowest system cost would be obtained if the operational costs of the WTE facility during the first period and the ratio of the generated residue are at their low levels. Figure 4.16 explains the interaction plots for the ratio of residue and the related revenue generated from the WTE facility. When the ratio is at its low level, the system cost would decline from 3.46×10^8\$ to 3.35×10^8\$ for the lower bound if the revenue increases from 15 to 25 \$/tonne. Thus, the lowest system cost can be obtained if the ratio of residue is at its low level and the

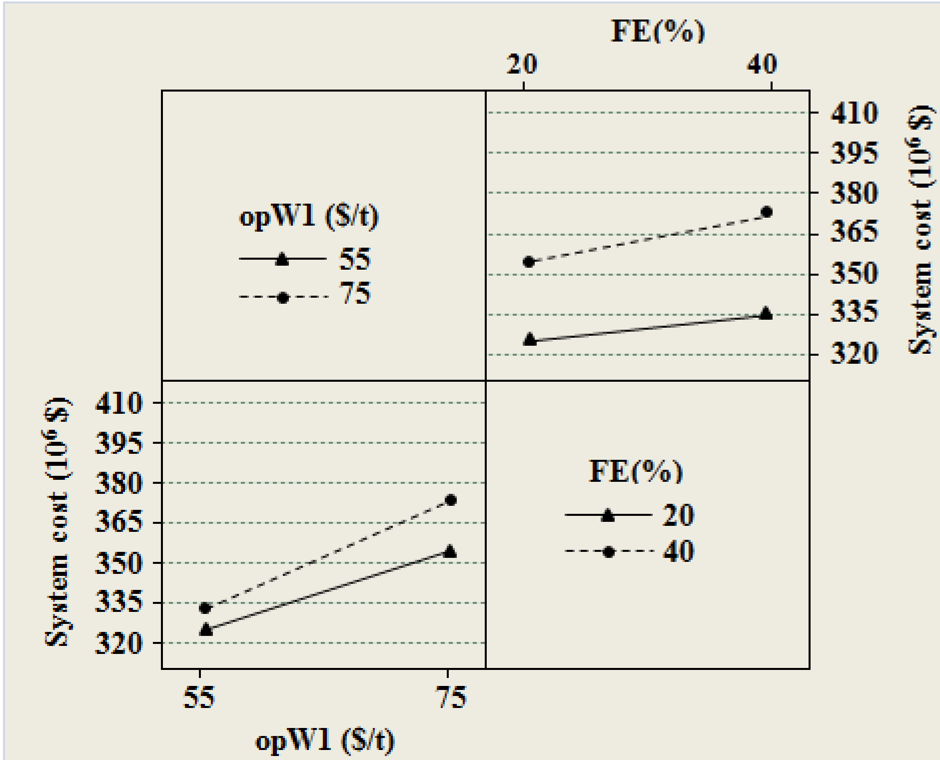

Figure 4.14 Interaction plot of LQ (opW1 and FE) to the lower bound of the system cost of sub-scenario 1 under scenario 1

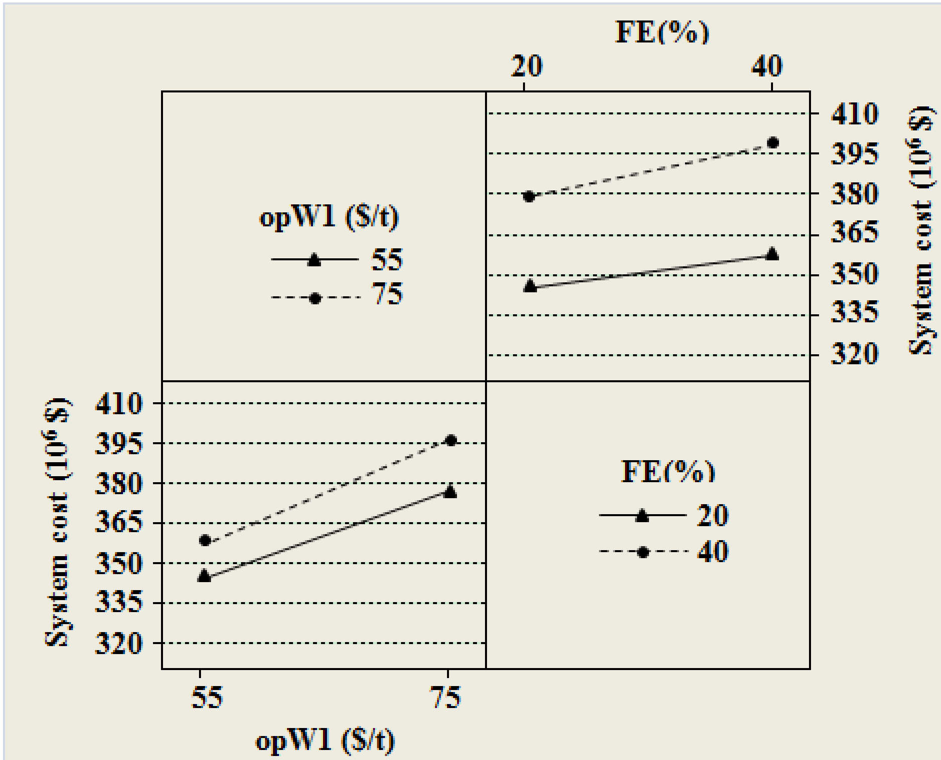

Figure 4.15 Interaction plot of LQ (opW1 and FE) to the upper bound

of the system cost of sub-scenario 1 under scenario 1

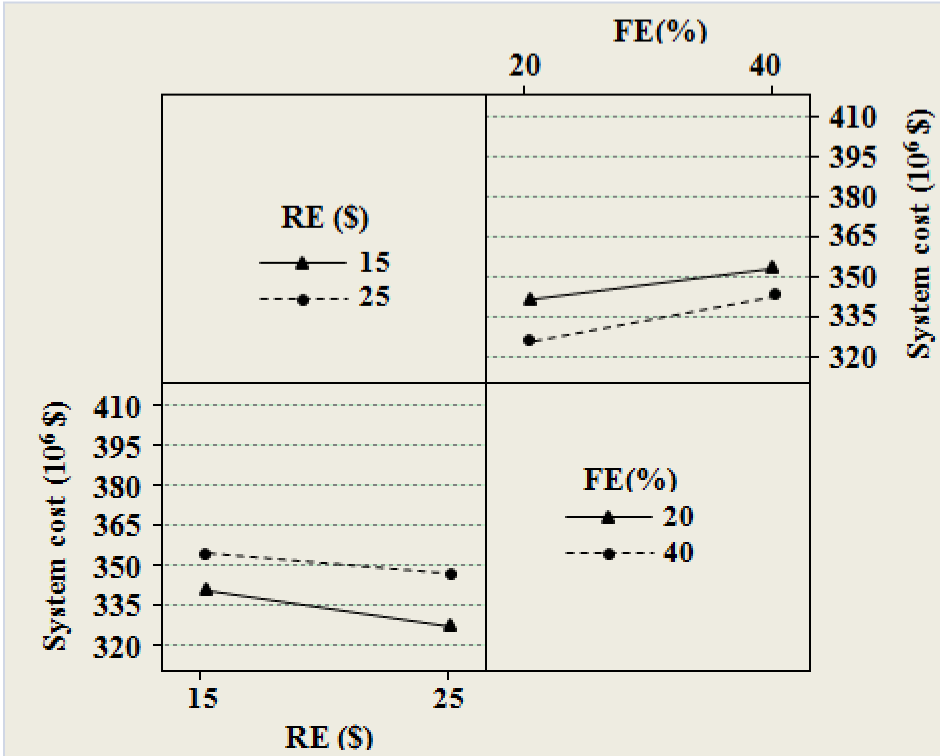

Figure 4.16 Interaction plot of QS (FE and RE) to the lower bound of the system cost of sub-scenario 1 under scenario 1

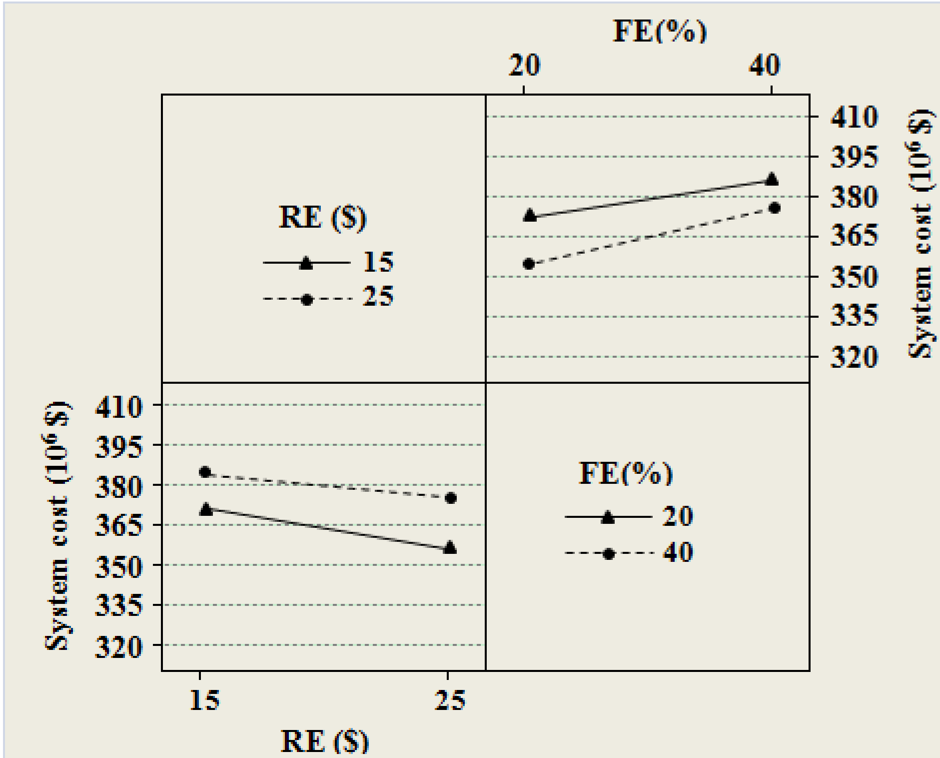

Figure 4.17 Interaction plot of QS (FE and RE) to the upper bound

of the system costs of sub-scenario 1 under scenario 1

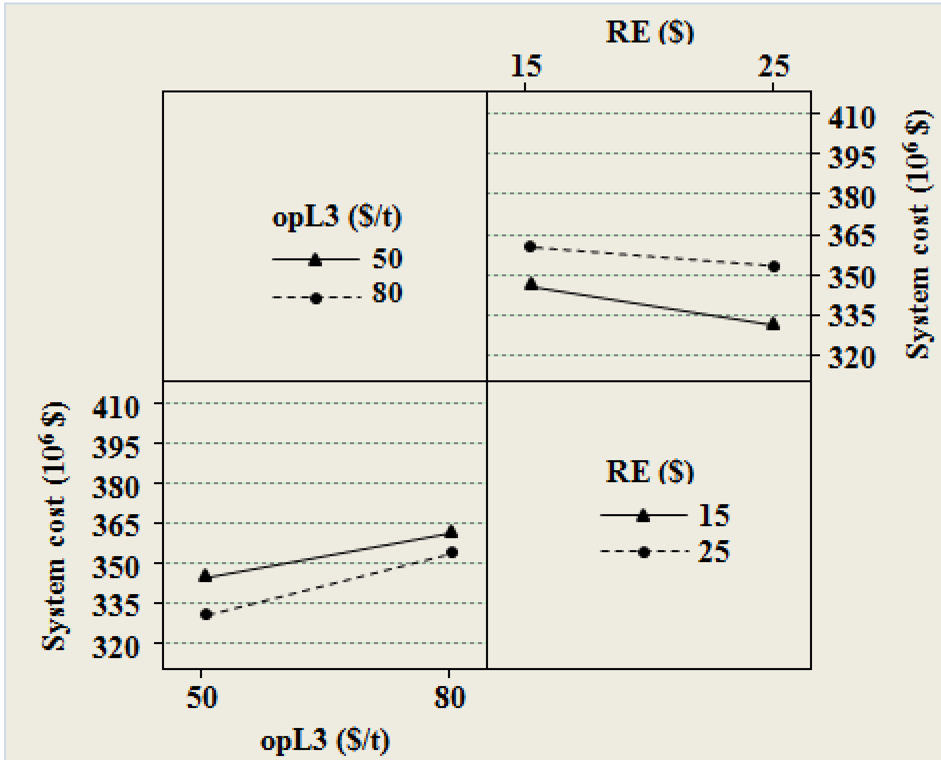

Figure 4.18 Interaction plot of OS (opL3 and RE) to the lower bound of the system cost of sub-scenario 1 under scenario 1

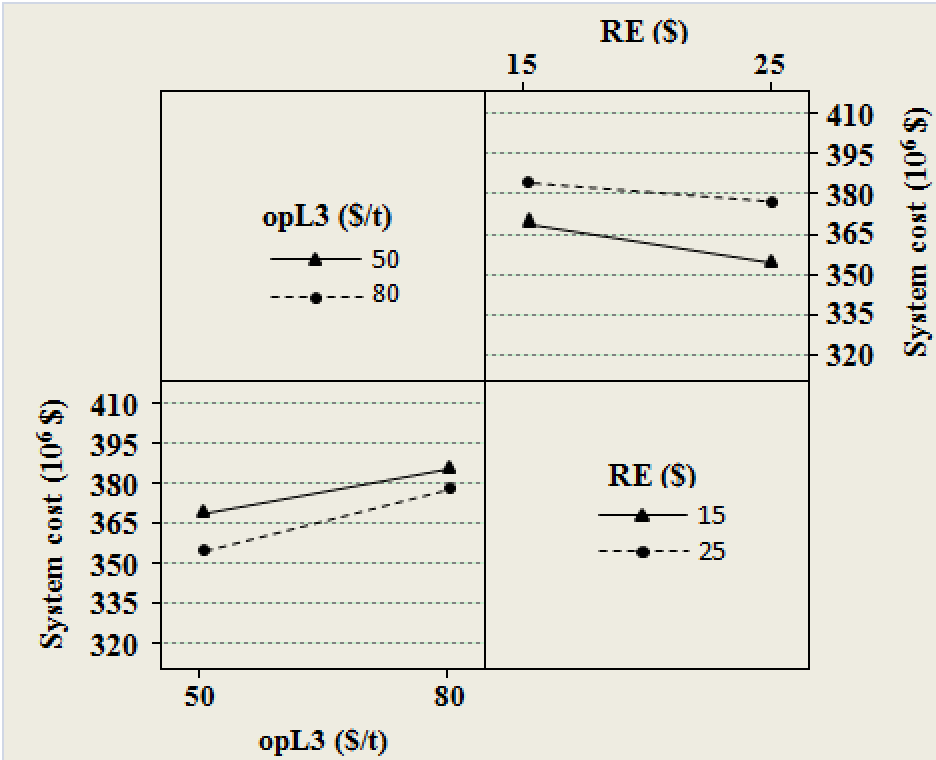

Figure 4.19 Interaction plot of OS (opL3 and RE) to the upper bound of the system cost of sub-scenario 1 under scenario 1

generated revenue is at its high level. Figure 4.18 indicates that when the revenue generated from the WTE facility is at its high level, then, the lower bound of the system cost would decrease from 3.55×10^8\$ to 3.31×10^8\$ if the operational costs of the landfill during the third period decrease from 80 to 50 $/tonne. Therefore, the lowest system cost would be obtained if the operational costs of the landfill are at their low levels and the revenue generated from the WTE facility is at its high level. For all of the above two-factor interactions, similar trends were discovered for factor interactions on their lower bounds and upper bounds of the system costs despite the fact that those generated system costs are much higher for the upper bounds compared to that of their lower bounds.

4.4 Discussion

In municipal solid waste management systems, significant uncertainties exist in the system components such as waste generation rates and the operational costs of the treatment facilities. In order to reflect the robustness of the system, dual intervals are adopted when the distributional information of the uncertain parameters is unavailable. By using dual intervals, different scenarios can be provided for decision makers in terms of analyzing the trade-offs between system cost and system reliability. In real-world applications, uncertain parameters of a system may vary among different scenarios. On one hand, a given factor may have significant influence on the system output under certain conditions while other factors have no effects. On the other hand, the given factor may contribute a lot to the system output as a single factor, but its interrelationships with another factor may have little effect on the system output. Therefore, it is necessary to analyze significant factors and their interactive effects on the system output.

Factorial analysis is effective in identifying significant factors and analyzing their joint effects on the system performance. In factorial analysis, various factors as well as their changes can be examined together. Therefore, the proposed FDIP method is an efficient way to not only tackle uncertain parameters expressed as dual intervals but also to identify the potential factors influencing the system performance, as well as their interactions on the system output, providing valuable information for decision makers.

It has to be pointed out that limitation could occur when dealing with real-world applications since the number of uncertain parameters may be too large, resulting in tedious efforts in estimating the effects. Thus, careful selection of the system parameters based on decision makers' implicit knowledge is highly suggested in order to perform factorial analysis.

4.5 Summary

In this study, a factorial dual-interval programming (FDIP) method was proposed through incorporating factorial analysis and dual-interval linear programming into a general framework to support municipal solid waste management systems under uncertainty. The proposed method is capable of: 1) tackling uncertainties expressed as single intervals and dual intervals in the objective function and their constraints, and 2) improving upon the existing dual-interval linear programming model by allowing uncertain parameters to be examined directly in terms of their individual and interactive effects on the lower bound and upper bound of the system output under various scenarios.

The proposed FDIP method has been applied to a case study on the planning of a municipal solid waste management system under uncertainty. It focused on identifying significant parameters and their joint effects on the minimized system cost. Results of the case study indicated that reasonable solutions of waste-flow allocation patterns were generated. This would assist decision makers in identifying desired waste-flow allocation schemes and considering trade-offs between system cost and system reliability. Moreover, through factorial analysis, several significant parameters were identified and their joint effects were analyzed according to the lower bound and upper bound of the system cost under different scenarios. These findings enabled decision makers more support in decision-making.

Although this study is the first attempt to integrate factorial analysis and a dual-interval linear programming model into a general framework to support municipal solid waste management systems under uncertainty, the proposed method can comprehensively reflect the uncertainties in both decision variables and modeling parameters. The results suggested that it could also be applicable to other environmental resources management problems. Further studies could be extended to the performance of stochastic factorial analysis where multiple uncertainties can be analyzed through more advanced probabilistic inference.

CHAPTER 5

CONCLUSIONS

5.1 Summary

(1) In this research, a dual-interval two-stage mixed-integer inexact-chance-constrained (DITMIC) linear programming method was developed and applied to a case study of water resources management under multiple uncertainties. The proposed DITMIC method could not only deal with various uncertainties expressed as intervals and probability distribution but also reflect dynamic features of various policy scenarios, associated with different levels of economic penalties, when the pre-regulated flood-diversion targets were violated. In DITMIC, the concept of dual interval was introduced into the optimization process when the acquired information was highly uncertain and could not be used to construct probability density functions and/or fuzzy membership functions. Moreover, the concept of distributions with interval-valued probability was introduced in the constraints' right-hand-sides in order to tackle uncertainties that were expressed in multiple forms. In general, the DITMIC method was able to provide interval solutions under different risk levels of violating the constraints, leading to in-depth analysis regarding the trade-offs between economic consequence and system reliability. The developed DITMIC method could provide reasonable plans on flood-diversion patterns and capacity-expansion schemes in an environment containing multiple regions, various flood flow levels, and diverse capacity-expansion options. Decision alternatives could be provided in for decision makers to identify desired flood-diversion plans according to their implicit knowledge towards future conditions.

(2) A factorial dual-interval programming (FDIP) method was proposed for planning municipal solid waste management systems under uncertainty. The FDIP method can tackle uncertainties expressed as single and dual intervals in the objective function and their related constraints. The FDIP improves upon the existing dual-interval linear programming method by allowing multivariate factorial analysis to be introduced into the conventional optimization framework. Thus, individual effects of the input parameters, as well as their interactive effects, could be identified and analyzed under various scenarios. Reasonable solutions were generated, which would assist decision makers to identify desired waste-flow allocation schemes and analyze trade-offs between system cost and system reliability.

5.2 Research achievements

(1) The DITMIC method was developed for the planning of flood-diversion management systems under multiple uncertainties. Compared with conventional optimization methods, the DITMIC method had the following advantages: 1) it could reflect uncertainties expressed as intervals, dual intervals, probability distributions, and interval-valued probability distributions; 2) pre-regulated flood-diversion targets could be integrated into the optimization process and the economic consequences of violating the system constraints could be also reflected; 3) it was able to reflect dynamic features of capacity-expansion planning when multiple regions, different flood flow levels, and various capacity-expansion options are involved; 4) reasonable solution variables could be generated in both binary and continuous formats; 5) in-depth information could be provided on policy analysis with regard to various levels of economic penalties when the pre-regulated flood-diversion targets are violated; 6) decision alternatives could be

provided based on the interpretation of the results. Thus, decision makers would have more options to choose from, and desired flood-diversion plans could be identified.

(2) The proposed FDIP method was a first attempt to integrate factorial analysis and dual-interval linear programming within a general framework. It was applied to the planning of municipal solid waste management systems under uncertainty. FDIP is capable of reflecting uncertainties expressed as intervals and dual intervals. Moreover, individual effects of the uncertain parameters and their interactions could be identified through multivariate factorial analysis. Individual and/or interactive effects that are of significant influences could be examined in order to provide decision makers with in-depth decision-support information. The proposed FDIP method was applied to a case study of municipal solid waste management. Reasonable solutions were generated in the form of interval and/or dual interval. Moreover, interrelationships embedded in the modeling system could be unveiled, which provided a useful basis for supporting sound environmental management.

5.3 Recommendations for future research

(1) In this research, the developed methods were applied to the planning of environmental management systems under uncertainty. In these methods, only linear relations among various decision variables were considered in the objective functions and their related constraints. However, in real-world applications, planning of environmental management systems involves many nonlinear relations and interactions that exist in the system components (Yeh, 1985; Barros et al., 2003). As a result, nonlinear optimization methods under uncertainty need to be developed to deal with such factors.

(2) Planning for environmental management systems involves many complexities and uncertainties regarding the system components, and the required data for such planning were often extensive. Although most of the required data were quite accurate and could be expressed as deterministic numbers, interval numbers with deterministic lower and upper bounds, and probability distributions, others were highly uncertain. Therefore, it was encouraged to improve the reliability on the generated solution variables by further verifying and investigating the input data (Krippendorff, 1970; Meeker and Escobar, 1998).

(3) When the number of uncertain parameters is too high in large-scaled problems, the proposed methods are often limited in their abilities to provide competent solutions. In particular, if the number of uncertain parameters is significantly large, the most concerning factors must be identified first, based on decision makers' implicit knowledge as well as their experiences. Then, factorial analysis can be performed to discover the interrelationships among various uncertain inputs.

(4) The developed mathematical programming methods can be extended to other applications involving multiple uncertainties, such as water quality management, air pollution control planning, and energy systems optimization.

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