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Original Research

An Inexact Sequential Response Planning Approach for Optimizing Combinations of Multiple Floodplain Management Policies

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Abstract

This study proposes an inexact sequential response planning (ISRP) approach for floodplain management on the basis of two-stage stochastic programming techniques. It can facilitate rapid response decision making for upcoming severe flood disasters by efficiently operating available multiple control measures in a quantified manner. The case study considers a floodplain management problem where decision makers want to obtain a cost-effective combination of multiple floodplain management policies (i.e. constructing hydraulic engineering, flood diversion) for coping with the upcoming flooding disasters with various severity levels. Optimal management strategies obtained from ISRP are analyzed, following by the demonstration of extending potentials.

Keywords: floodplain management, flood control, uncertainty, two-stage, sequential response planning

Introduction

With increasing development in floodplains, less soil is available to absorb floodwater, leading to more frequent occurrences of flood disasters. Such frequently-occurring disasters have directly and indirectly resulted in the death of a large number of people, plus billions of dollars of infrastructural damage [1-3]. To ameliorate impacts of flooding disasters, various floodplain management policies have been used individually or simultaneously to pursue the most cost- and flood-control-effective strategies. Historically, many researchers have attempted to use mathematical programming tools to assist in determining optimum management schemes [4-9].

Day and Weisz [10] developed a linear programming model for urban floodplain management of the Tucson situation; the optimum combination of flood control and land development policies was identified by the model. Hopkins et al. [11] proposed an interdependent land use allocation model for the Hickory Creek watershed; the work also compared land-use allocation policies in terms of aggregate economic rent and the interdependence between floodplain land use and upstream land use. Needham et al. [12] formulated a mixed integer linear programming model for flood control and applied it to the reservoir system analysis of three U.S. Army Corps of Engineers' projects on the Iowa and Des Moines rivers. Olsen et al. [13] presented a dynamic floodplain management model to address nonstationary conditions, including land-use changes, channel modifications, economic development, and climate change

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and variability; by applying the model to Chester Creek, Pensylvania, an optimal policy was established for determining whether levee building or levee replacement should be implemented. Using fuzzy set theory and fuzzy logic, Akter and Simonovic [14] advanced a methodology to capture the views of multiple stakeholders of the Red River Basin in Manitoba, Canada; the results showed alternative ways of soliciting the opinion of stakeholders and aggregating those opinions in multi-objective decision-making. Haynes et al. [15] integrated socio-economic analysis into a decision-support framework for flood risk management in Scotland; they considered the potential hazards, exposure, and vulnerability of a residential development to flooding disasters, and predicted the social impact by using statistical evaluation of census data.

Recently, recourse problems have increasingly received much attention in floodplain management, when corrective actions are necessary against the predefined targets (or capacities) due to the randomness of flooding events [16]. Two-stage stochastic programming (i.e. TSP) approaches have shown its capability to address such problems [17-23]. For example, Lund [17] presented a TSP formulation for minimizing the expected value of flood damage and costs given a flow or stage frequency distribution; a case study was subsequently used to demonstrate the model's performance in developing optimum permanent and emergency floodplain management options. Glamore and Indraratna [23] incorporated two-stage flood estimation into a water quality decision support tool (DST); the tool was applied to a field site in southeastern New South Wales (NSW) to simulate tidal restoration in a flood mitigation drain affected by acid sulfate soils leachate.

A challenge in face of many decision makers is how to address the parameter uncertainty encountered in analyses of floodplain management decisions [24], such as temporarily varied economic-related parameters, quantities of the floodwater to be handled, and available capacities of flood-control infrastructure. Such a challenge is particularly complicated when no substantial data can be available to derive probability of many parameters [25]. Under this situation, bounded, fuzzy and soft information have been frequently used to quantify such an uncertainty in modeling inputs and outputs [25-33]. For example, Franks et al [35] incorporated a generalized likelihood uncertainty estimation methodology into the calibration process of TOPMODEL (a topography based hydrological model proposed by Beven and Kirkby in 1979); in the calibration, six key parameters including effective lateral saturated transmissivity and channel routing velocity were expressed as intervals with their lower and upper limits being provided. Schulz et al. [36] applied a fuzzy inference method to communicate imprecise thermodynamic parameters into chemical equilibrium calculations of aqueous systems; fuzzy numbers with different shapes of membership functions were used to express imprecision in a non-probabilistic sense. Khadam and Kaluarachchi [37] presented a framework using the method of order of importance to incorporate soft information to describe the relative accuracy in flood frequency and in-stream flow. More similar efforts have been shown in Mpimpas et al. [38].

Results from these studies have shown that bounded values, fuzzy sets, and soft information can be useful in quantifying uncertain parameters without knowing their distribution information. In the past decades, a couple of floodplain management models with assistance of interval analysis have been proposed which enabled interval information to be translated into TSP frameworks [39-41]. Although they could be useful in handling interval-valued parameters and recourse issues, the real-world circumstances were not effectively reflected. In the existing studies, for example, diversion was their exclusive option for coping with flooding disasters, and optimally diverting the floodwater is of major concern. In most cases, they could only advise (1) whether or not one region should be flooded, or (2) which region was better to be flooded in order to avoid more capital losses when flood disasters occurred. The effectiveness of such a system and the resulting management strategies is thus questionable. In comparison, if multiple flood-control measures were considered, the systems can then be much safer to defend against severe flooding disasters, which also approach real-world circumstances.

In response to the above considerations, this study aims to develop a new inexact sequential response planning (ISRP) approach for floodplain management. It will be able to (1) support identification of optimal combinations of multiple floodplain management policies, and (2) handle uncertainty associated with interval- and stochastic-valued parameters. Since the approach will be developed based on the concepts of TSP and interval analysis, it can be solved through a two-step interactive algorithm from which a set of flexible interval solutions can be obtained. The approach will be applied to a floodplain management case to demonstrate its capability in dealing with uncertain parameters and recourse issues, as well as interactions among multiple response actions to flooding disasters.

Methodology

Typical TSP problems can be characterized by two essential stages: uncertain modeling inputs expressed as probabilistic distributions at the early stage of decision making, and subsequent decisions generated at the later planning stage [19, 39]. The first-stage decision is made before the values of random variables are clearly known; afterward, a second-stage decision (or say, recourse decision) is made after the random events occur. In most floodplain management systems, the flood-control measures can be categorized into two groups: permanent floodplain management actions (e.g., constructing reservoirs and flood walls, raising foundations, changing land-use schemes), and emergency response actions (e.g., levee sandbagging, floodwater diversion) [17]. Permanent actions are first conducted to defend against a flood. However, they may run short of capacity for handling increasingly serious disasters due to the rise of upcoming flows. Emergency responses thus need to be activated to mitigate the surplus damage arising from the insufficiency of permanent flood-control measures. To support the decisions sequentially made at two levels (i.e. for instructing permanent and emergency responses actions), TSP is introduced as the basis for ISRP formulation.

Take a watershed system where different severity levels of flood disasters occur frequently. To reduce the associated damage, permanent engineering and emergency responses are both under consideration. For the former, constructing a reservoir with an appropriate water-storing volume (to be determined) is the major option. For the latter, several diversion regions are available to deal with the surplus floodwater. The problem is thus to obtain an optimal combination of these floodplain management options, with an objective of minimizing the total cost for implementing the actions. A sequential response planning formulation is proposed in view of the probabilistic feature of the upcoming floodwater quantity. In the formulation, whether or not the reservoir project (and if yes, what capacity should be designed) is first decided in terms of the severity level of flooding disasters. After that, a second-stage decision needs to be made on how to take an emergency response when the first-stage action cannot satisfy the flood-control demand. Where information about part of the system parameters is quantified as intervals, the problem can be formulated as the following inexact sequential response planning (ISRP) problem:

$$\min f^{\pm} = \sum_m CP_m^{\pm} \cdot X_m + E\left[\sum_n CE_n^{\pm} \cdot Y_{nQ}^{\pm}\right] \qquad (1)$$

subject to:

$$\sum_m WP_m^{\pm} \cdot X_m + \sum_n Y_{nQ}^{\pm} \geq Q^{\pm} \qquad \forall j \qquad (2)$$

$$Y_{nQ}^{\pm} \leq Y_{\max n}^{\pm} \qquad \forall j \qquad (3)$$

$$0 \leq \sum_m X_m \leq 1 \qquad (4)$$

$$X_m = \text{binary varible} \qquad \forall m \qquad (5)$$

...where: f – system cost, m – index for permanent engineering, n – index for emergency response actions, CP_m – cost for projecting permanent engineering m, CE_n = cost for implementing emergency response action n in handling a unit of floodwater, $E\,[\cdot]$ – expected value of a random variable, X_m = integer decision variables corresponding to the projection of permanent engineering m, Y_{nQ} – decision variables corresponding to the floodwater volume handled by emergency response action n when the floodwater quantity to be handled is Q, WP_m = quantity reduction of floodwater arising from the projection of permanent engineering m, $Y_{max\,n}$ – maximum capacity of emergency response action n in handling floodwater, superscript "±" represents the corresponding parameters/variables presenting interval characteristics. To solve this problem, continuous random variable Q is approximated by a set of discrete random variables by letting Q take values q_j with probability p_j. The detailed solution procedures can be referred to Huang and Loucks [18].

Table 1. Probability of flooding events and the associated floodwater volumes to be handled.

	Upcoming floodwater volume (10^6 m^3)	Probability
Low	[5.3, 8.5]	0.06
Low to medium	[8.6, 12.0]	0.11
Medium	[12.1, 15.1]	0.60
Medium to high	[15.2, 18.6]	0.18
High	[18.7, 21.6]	0.05

Table 2. Characteristics of hydraulic engineering.

	Small reservoir	Big reservoir
Structuring cost ($\$10^6$/project)	[180, 210]	[230, 250]
Capacity of storing floodwater (10^6 m^3/project)	[2.3, 2.7]	[3.0, 3.2]

Table 3. Efficiency and economic data of diversion actions.

	Diversion costs (\$/m^3)	Maximum capacity (10^6 m^3)
Region 1	[80, 100]	5.0
Region 2	[95, 110]	7.5
Region 3	[90, 115]	6.4

Case Study

Statement of the Problem

The developed approach is applied to a floodplain management problem, wherein a river with a limited water conveyance capacity is considered. Flood disasters occur in most wet seasons under different severity levels (Table 1). To reduce the potential damage to downstream human society and ecological systems, the floodplain manager plans to implement a set of flood-control measures. These might include (1) hydraulic projects of structuring reservoirs over the channel, and (2) emergency response actions of diverting the overflow floodwater to several adjacent regions when the first mitigation action cannot completely eliminate the damage. Two reservoirs with different water-storing capacities (Table 2) are under consideration, and three regions are available for supporting potential flood-diversion actions. The respective capacities and implementation costs, as well as the maximum capacities of diversion regions are shown in Table 3. From an economic perspective, all of these measures can hardly be simultaneously implemented, resulting in the following two problems. One is whether the hydraulic engineering needs to be projected;

Table 4. Solutions to ISRP and TSP models.

	First-stage decision variables (binary variables) (ISRP/TSP)		Second-stage decision variables (continuous variables) (10^6 m^3) (ISRP/TSP)	
	Constructing small reservoir (X_1)	Constructing large reservoir (X_2)		
Low (j = 1)	No (X_1 =0/0)	Yes (X_2 =1/1)	[2.3, 5.0]/3.8	Diversion region 1
Low to medium (j = 2)			5.0/5.0	
Medium (j = 3)			5.0/5.0	
Medium to high (j = 4)			5.0/5.0	
High (j = 5)			5.0/5.0	
Low (j = 1)	No (X_1 =0/0)	Yes (X_2 =1/1)	[0, 0.3]/0	Diversion region 2
Low to medium (j = 2)			[0, 3.2]/0	
Medium (j = 3)			[0, 2.8]/0	
Medium to high (j = 4)			[0.8, 4.0]/7.5	
High (j = 5)			[4.3, 7.0]/7.5	
Low (j = 1)	No (X_1 =0/0)	Yes (X_2 =1/1)	0/0	Diversion region 3
Low to medium (j = 2)			0.6/2.2	
Medium (j = 3)			4.1/5.5	
Medium to high (j = 4)			6.4/1.3	
High (j = 5)			6.4/4.55	
f ($\$10^6$)	[1010.97, 1552.97]/1257.80			

if yes, how much capacity should be designed. The other is how to cost-effectively divert the surplus floodwater to the three regions. These two decisions are subject to a minimum overall system cost.

In such a system, an amount of uncertain information exists, particularly in the following parameters:

(1) Economic-related parameters that vary temporally (e.g., costs for structuring conservancy projects, recovering flooded regions, and compensating affected communities)
(2) Quantities of the floodwater to be handled, which are in relation to the severity of flooding events, velocity of upcoming floodwater, and response time of local authorities
(3) Available capacities of flood-control infrastructures, which are intensely affected by real-time operating conditions

Since the variation ranges of these parameters are rather convenient to be identified based on historical data and expert experience, they are expressed as intervals in the following formulation.

Modeling Formulation

Let m = 1 and 2 be the reservoir with capacities of [2.3, 2.7] and [3.0, 3.2]$\times 10^6$ m^3, j = 1, 2, 3, 4, and 5 be the low, low-to-medium, medium, medium-to-high, and high severity levels of flooding disasters, and n = 1, 2, and 3 be diversion regions 1, 2, and 3, respectively. The decision variables include:

(1) The first-stage decision variables, i.e. binary variables X_m, indicating whether or not the hydraulic engineering needs to be projected
(2) The second-stage decision variables, i.e. continuous variables $Y_{nj}^{\pm}$, representing the volumes of floodwater diverted to each region under various severity levels of flooding.

Thus the problem can be solved by the following model:

$$\min f^{\pm} = \sum_{m=1}^{2} CP_m^{\pm} \cdot X_m + \sum_{j=1}^{5} p_j \sum_{n=1}^{3} CE_n^{\pm} \cdot Y_{nj}^{\pm} \quad (6)$$

subject to:

$$\sum_{m=1}^{2} WP_m^{\pm} \cdot X_m + \sum_{n=1}^{3} Y_{nj}^{\pm} \geq q_j^{\pm} \quad \forall j \in 1,2,...,5 \quad (7)$$

$$Y_{nj}^{\pm} \leq Y_{\max n}^{\pm} \quad \forall j \in 1,2,...,5 \quad (8)$$

$$0 \leq \sum_{m=1}^{2} X_m \leq 1 \quad (9)$$

$$X_m = \text{binary varible} \quad \forall m = 1,2 \quad (10)$$

The above model is then solved through the two-step interactive algorithm as described in section 2. Note that the model solutions can be interval or deterministic in relation to their sensitivity to the uncertain modeling inputs. The interval solutions indicate that the variables are sensitive to parameter uncertainty, while the deterministic ones imply their insensitivity to the interval inputs.

Result Analysis

Table 4 presents the optimal flood-control strategies obtained from ISRP. The identified two-stage decisions suggest how much capacity (i.e. [2.3, 2.7]×10^6 m^3, [3.0, 3.2]×10^6 m^3 or 0) should be designed for the reservoir and how the surplus floodwater deducted from the reservoir should be diverted to the three regions. In detail, the first-stage decision is suggested by the solutions of two binary variables, respectively corresponding to constructing the reservoir with small and large water-storage capacities. If both binary variables equal 0, then no reservoir needs to be projected. The second-stage decision is generated through the quantification of continuous variables, which links to the floodwater volume diverted to each region under different severity levels of flooding disasters.

The solutions show that the construction of a big reservoir is necessary to adapt to serious flooding disasters probably occurring in this area, although increased management cost would be required. After the first-stage deduction (i.e. [3.0, 3.2]×10^6 m^3 of floodwater), the surplus water would be diverted to the following three regions with various volumes according to the severity levels. For example, regions 1, 2 and 3 would be diverted 5.0 [0, 3.2], and 0.6×10^6 m^3 of floodwater under the low-to-medium flooding condition. These values would change to 5.0 [0.8, 4.0], and 6.4×10^6 m^3 when medium-to-high flooding occurs.

The lower-bound costs for constructing the reservoir and diverting floodwater (i.e. CP_m^- and CE_n^-) correspond to an optimal flood-control scheme with the most desired expected value of overall system cost (i.e. f_{opt}^-). In comparison, the upper-bound costs link to an optimal but higher than expected value of the objective (i.e. f_{opt}^+) under the most adverse condition (i.e., the related costs are imposed to be the highest values among their pre-regulated ranges). The optimal overall system cost is $[1010.97, 1552.97]×$10^6$, with respective shares of 18.72 and 81.28% on conducting the hydraulic engineering and emergency response actions. The values of f_{opt}^- and f_{opt}^+ provide two extremes of the overall system cost. As actual values of variables and parameters vary between their bounds, the practical system cost may correspondingly change between f_{opt}^- and f_{opt}^+.

The system-cost distribution can be obtained by dividing the total system cost by the cost of implementing each flood-control measure under different levels of flooding disasters (Fig. 1). Take the lower-bound objective-function inputs and the related outputs, for example. Under the low severity-level of flooding disasters, all system costs would be used to construct the reservoir and divert floodwater to region 1, with respective shares of 56 and 44% to the total cost. When the flooding disasters becoming severe, regions 3 and 2 would be sequentially considered to satisfy the increased flood-control demand. Accordingly, the ratio of the reservoir-construction cost to the total system cost is decreased. Particularly in response to the most severe flooding disasters, as few as 14% of the system cost would be used for initializing the hydraulic engineering.

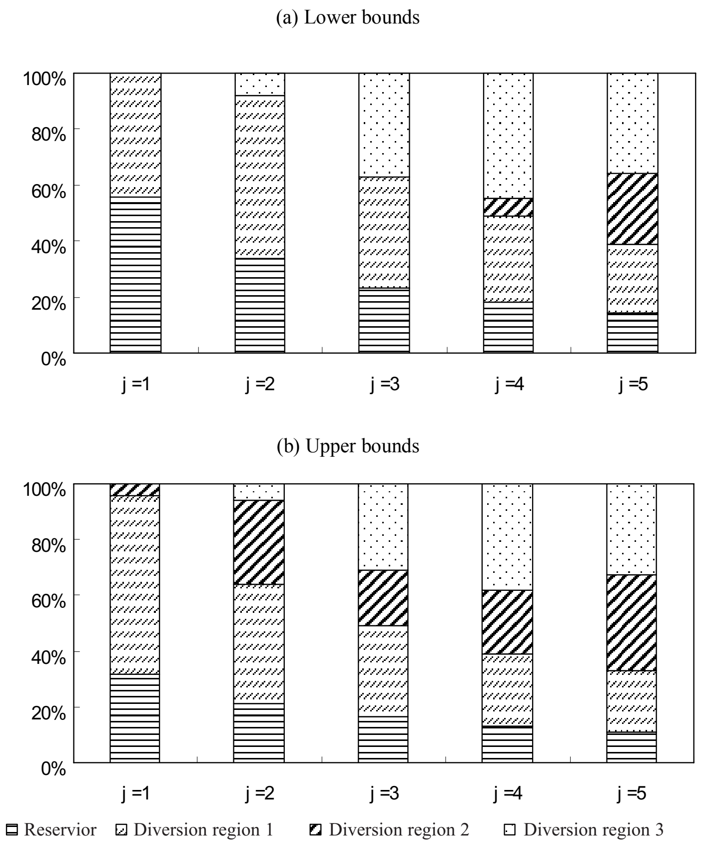

Fig. 1. System cost distribution.

Fig. 2 presents the utilization rates of diversion regions. Region 1 would be completely occupied in most cases when the floodwater volume is larger than [8.6, 12.0]×10^6 m^3 due to its lowest cost among three regions (Fig. 2a). The second fully-occupied diversion region would be region 3, when the severity level of flooding disasters is higher than medium (Fig. 2c). Region 2, however, would never be fully loaded in terms of its highest cost (Fig. 2b). Note that an intersection is observed in Fig. 2d under the low-to-medium flooding level. This is caused by the similar diversion costs of regions 2 and 3 (i.e. $[95, 110] vs. [90, 115]/$m^3$ floodwater diverted). The interactive solution method used in this study regulated that the first-desired solutions were incorporated into the following optimization process. This led to the priority of diverting floodwater to region 3 being generated under a cost-saving premise (as $CE_3^- \le CE_2^-$). Thus, the lower-bound output of region 3 is higher than that of region 2 (i.e. 0.6 vs. 0×10^6 m^3). Conversely, the upper-bound inputs (i.e. CE_n^+) impose a region-2-priority output (as $CE_2^+ \le CE_3^+$), resulting in a large amount of floodwater being diverted to region 2. Since Fig. 2d is generated on a basis of average values, an intersection appears in association with the increased demand of handling more floodwater.

Flood-control efficiencies of the hydraulic project and emergency responses can also be obtained by comparing their respective floodwater-control volumes. Take the high severity level of flooding disasters, for example. The reservoir would mitigate 15.38% of the upcoming floodwater, leading to a surplus of [15.7, 18.4]×10^6 m^3 to be further diverted. All available capacities of regions 1 and 3 would be utilized to accommodate 24.81 and 31.76% of the deducted floodwater, respectively. The diversion task remained for region 2 would then be of handling 43.43% of floodwater, indicating a capacity of [0.5, 3.2]×10^6 m^3 being still unused.

To clarify the difference between the proposed approach and conventional deterministic ones in dealing with floodplain management problems, the case is also solved by conventional two-stage stochastic programming (i.e. TSP) formulation with deterministic modeling inputs. Through replacing the interval parameters with mid-values of their lower and upper bounds, a set of deterministic solutions to the problem can then be obtained through a conventional TSP approach (Table 4). It can be found that the solutions to binary variables keep the same from two models, while those to continuous variables are mostly different. Some of the TSP solutions fall within the range of inter-

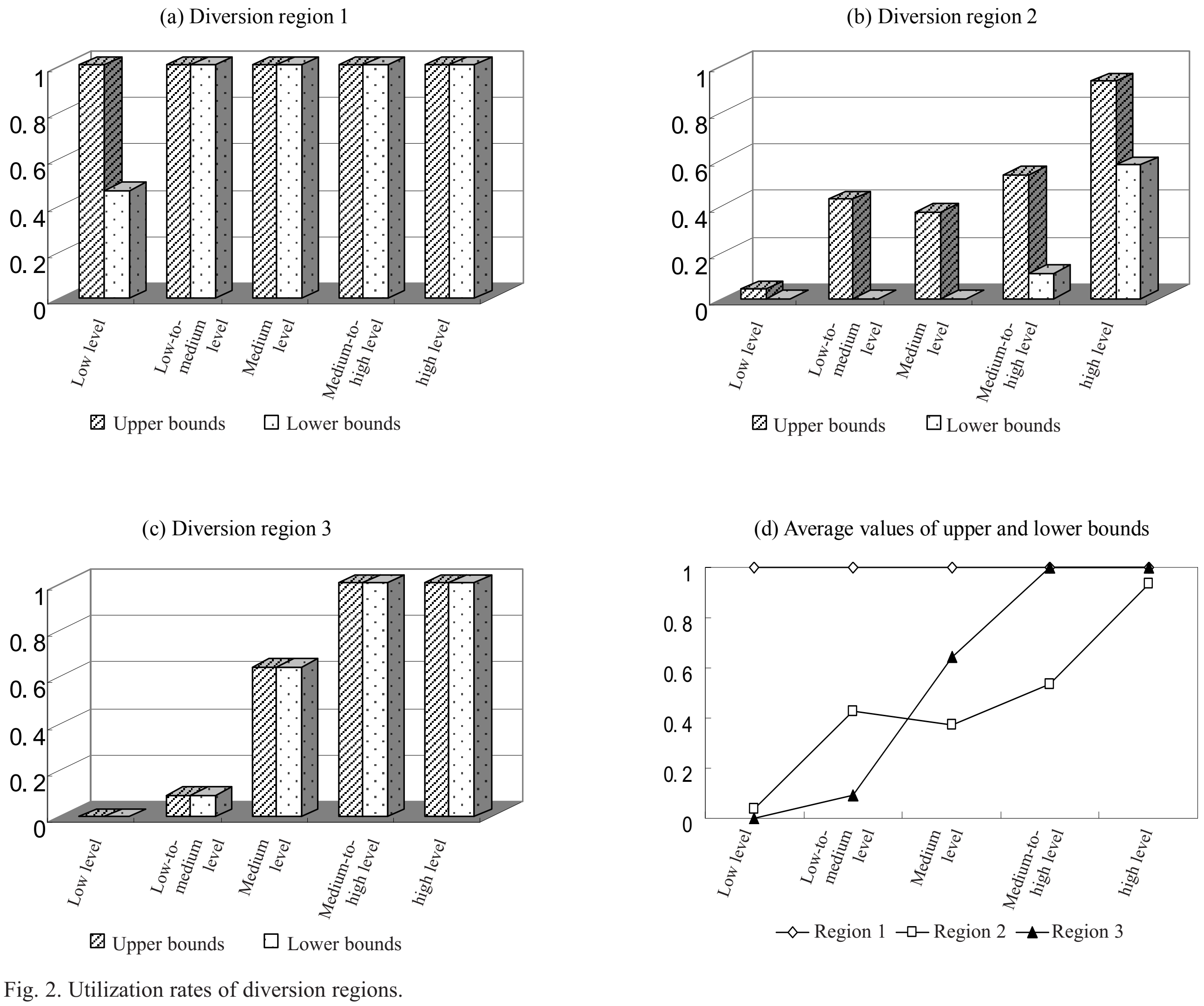

Fig. 2. Utilization rates of diversion regions.

val ones while the others are completely out of bounds, indicating a significant impact of parameter uncertainty on the resulting solutions. The objective value is also different between two modeling results. Although the TSP solution of objective function is involved within the ISRP solution, it is indeed one of the representative scenarios of the problem and can only provide less implication to decision makers than that the ISRP model.

Sensitivity analysis of parameters affecting system outputs is also undertaken by dynamically adjusting the modeling inputs. According to the pre-regulated parameters and computational optimization, a big reservoir is suggested in terms of the cost-saving goal and flood-control demand. However, if decision makers have to construct a small reservoir due to many practical reasons, then the cost for conducting this engineering needs to be curtailed from \$ [180, 210]×10^6 to \$[166, 194]×10^6. It would impose a minimum overall system cost of \$ [1010.35, 1554.46]×10^6. Although the modeling input of $CP_1^{\pm}$ under this condition is less, the optimal objective-function value is greater than that under the original inputs. This indicates the effectiveness of ISRP in searching for optimal solutions. Alternatively, the construction of a big reservoir is inevitable unless it would take as much as \$[244, 266]×10^6 (compared with the original \$[230, 250]×10^6); this would lead to an increased system cost of \$ [1024.35, 1570.46]×10^6.

Discussion

In this study, TSP was introduced to the proposed modeling formulation in order to facilitate two-stage decision making, respectively corresponding to the projection of hydraulic engineering and the scheme of the following emergency response actions. Previously, there were several TSP applications in floodplain management problems [17], although few of them aimed to tackle the uncertainty existing in hybrid interval- and stochastic-values parameters. Maqsood et al. [42] proposed an ITSP method for flood-diversion problems, followed by a few studies attempting to take fuzziness of modeling constraints into optimization accounts. In these studies, however, diversion is the exclusive option in flood control, resulting in the first-stage decision of identifying optimal floodwater-diversion targets. This can hardly be useful for dealing with most long-term planning problems, where a variety of defensive measures need to be considered. The incapability of these efforts thus exhibits in handling comprehensive floodplain management problems when decisions regarding the implementation of both structural actions and emergency responses need to be made.

The Monte-Carlo simulation approach is frequently employed to deal with continuous random variables. In the approach, a number of repeated simulations should be run, with each one outputting the floodwater level under one realization of random variables. In this study, we did not use the Monte-Carlo simulation approach to deal with random parameters; instead, they were discretized to a set of random events, with each one assigned to a probability indicating the chance of event occurrence. The possible floodwater level is then estimated under each of the realizations of the discretized random event. Therefore, the resulting flood management cost under randomness is then expressed as the reservoir-developing cost for the first-stage decision, plus floodwater-diverting cost for the second-stage decision. The advantage of this approach lies in the simplification of mathematical formulations, which does not introduce complex nonlinear objective or constraints. Thus, many of the previous studies have used such a method to deal with random parameters in decision making [17, 44].

The expansion of diversion regions has been a major concern in floodplain management [12, 44]. This study, however, did not consider expansion issues in the modeling formulation. This was based on a premise that the existing capacities of flood-control measures would be sufficient enough. This may be improved when expansions of the existing infrastructures are required for adapting to severe flooding. Meanwhile, this study considered two types of floodplain management policies; however, more options may be employed in real-world systems where much severe flooding disasters frequently occur. Under such circumstances, the problem becomes rather complex. For example,

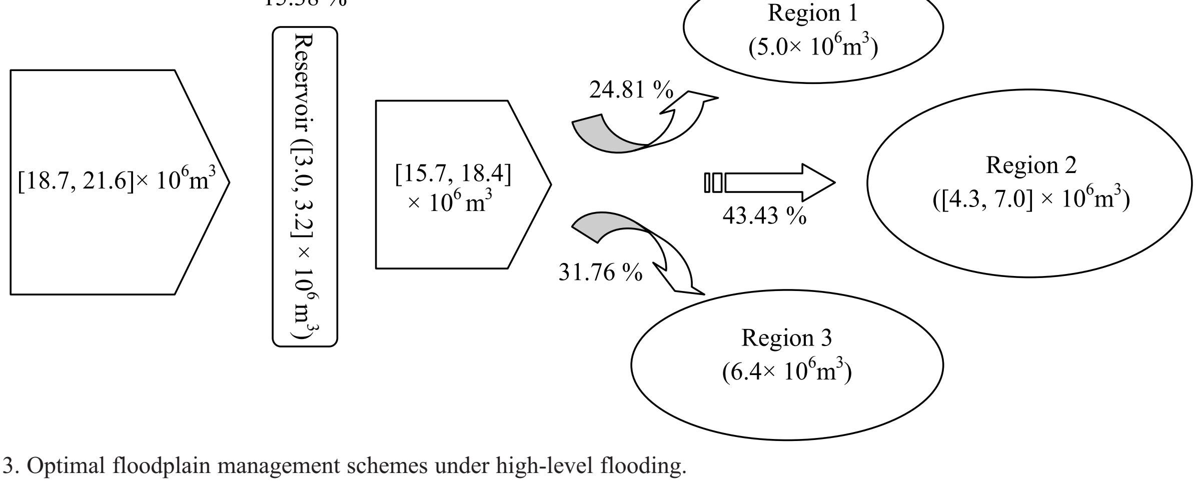

Fig. 3. Optimal floodplain management schemes under high-level flooding.

when a flood disaster occurs, a reservoir could be firstly operated to mitigate the damage downstream. If the surplus floodwater volume after deduction is out of the acceptable capacity of downstream receptors, then the second defensive work would be performed, such as sandbagging of levees and heightening levee monitoring [17]. When these implementations fail to eliminate the damage, more actions would have to be activated (e.g., flood diversion and evacuations if necessary). Apparently, these decisions need to be made sequentially, and the subsequent decision cannot be identified unless the preceding action has taken effect. Then multi-subsequent response planning approaches may be needed to handle such complex problems.

Conclusions

An inexact sequential response planning approach was proposed for floodplain management under interval- and stochastic-parameter uncertainty. It can be used for identifying the most effective and economy-efficient combination of flood-control measures in terms of historical data (i.e. probability of flooding occurrence and the related floodwater quantities). Results from the case study indicated that the approach could be helpful in facilitating decision making for a rapid response to upcoming severe flooding disasters by efficiently operating available control measures in a quantified manner. The limitation and extension potentials of this approach also were discussed.

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