European Journal of Operational Research 249 (2016) 258–269

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

Risk-based factorial probabilistic inference for optimization of flood control systems with correlated uncertainties

S. Wang, G. H. Huang*

Faculty of Engineering and Applied Science, University of Regina, Regina, Saskatchewan S4S 0A2, Canada

ARTICLE INFO

Article history:
Received 15 September 2014
Accepted 13 August 2015
Available online 22 August 2015

Keywords:
Flood control
Multivariate inference
Probabilistic optimization
Risk

ABSTRACT

In this paper, a risk-based factorial probabilistic inference method is proposed to address the stochastic objective function and constraints as well as their interactions in a systematic manner. To tackle random uncertainties, decision makers' risk preferences are taken into account in the decision process. Statistical significance for each of the linear, nonlinear, and interaction effects of risk parameters is uncovered through conducting a multi-factorial analysis. The proposed methodology is applied to a case study of flood control to demonstrate its validity and applicability. A number of decision alternatives are obtained under various combinations of risk levels associated with the objective function and chance constraints, facilitating an in-depth analysis of trade-offs between economic outcomes and associated risks. Dynamic complexities are addressed through a two-stage decision process as well as through capacity expansion planning for flood diversion within a multi-region, multi-flood-level, and multi-option context. Findings from the factorial experiment reveal the multi-level interactions between risk parameters and quantify their contributions to the variability of the total system cost. The proposed method is compared against the fractile criterion optimization model and the chance-constrained programming technique, respectively.

1. Introduction

Flooding is the most frequent and expensive natural disaster in Canada, which is typically caused by heavy rainfall, rapid melting of a thick snow pack and ice jams. In June 2013, extensive rainfall brought massive flooding across Alberta located in western Canada, affecting tens of thousands of families throughout the region, resulting in the loss of four lives, and displacing over 100,000 people from their homes (WaterSMART, 2013). It is estimated that the total damage of Alberta's super flood will exceed $5 billion, which is the costliest disaster in Canadian history (Gandia, 2013). Recent accelerations in population growth, economic development, as well as changes in climate and land use patterns have been increasing risks and vulnerability to flood hazards.

Since losses cannot be avoided when a flood occurs, a sound flood mitigation plan is of vital importance for reducing flood damage. Optimization models play a crucial role in identifying effective flood mitigation strategies, which have been extensively used for flood management problems over the past decades (Braga & Barbosa, 2001; Labadie, 2004; Olsen, Beling, & Lambert, 2000; Unver & Mays, 1990; Wasimi & Kitanidis, 1983; Windsor, 1981). For instance, Needham, Watkins, Lund, and Nanda (2000) proposed a mixed-integer linear programming model to assist with the U.S. Army Corps of Engineers' flood management studies on the Iowa and Des Moines rivers. Wei and Hsu (2008) proposed mixed-integer linear programming models to solve the problem of the real-time flood control for a multireservoir operation system. Ding and Wang (2012) developed a nonlinear optimization approach for identifying the optimal flood diversion discharge in order to mitigate flood water stages in the channel network of a watershed. Karamouz and Nazif (2013) developed a multi-criteria optimization model to select best management practices for flood mitigation in urban watershed systems. Woodward, Gouldby, Kapelan, and Hames (2014) proposed a multiobjective optimization algorithm to determine an optimal flood risk mitigation strategy for a flood protection system. These methods were useful for identifying optimal flood mitigation schemes and reducing the risk of flood damage. Due to the inherent variability and unpredictability (randomness) of flood control systems, however, many parameters cannot be exactly identified; they are often modelled as random variables. As a result, conventional optimization methods would fail to cope with random variables appropriately.

In the past decade, a number of optimization techniques were proposed for addressing random uncertainties in water resources problems (Gaivoronski, Sechi, & Zuddas, 2012; Housh, Ostfeld, & Shamir, 2013; Pallottino, Sechi, & Zuddas, 2005; Wang & Huang, 2011, 2012, 2013; Zhou, Huang, & Yang, 2013). For instance, Bravo and Gonzalez (2009) developed a stochastic goal programming model for

* Corresponding author. Tel.: +1 306 585 4095; fax: +1 306 585 4855.
E-mail address: huang@iseis.org, gordonhuangevse@gmail.com (G.H. Huang).

http://dx.doi.org/10.1016/j.ejor.2015.08.023
0377-2217/

helping public water agencies allocate surface water among farmers and authorize the use of groundwater for irrigation under uncertainty. Chung, Lansey, and Bayraksan (2009) applied a robust optimization framework to design a reliable water supply system under parameter uncertainties. Wang and Huang (2014a) proposed a multilevel Taguchi-factorial two-stage stochastic programming method for supporting water resources management under interactive uncertainties. Among these methods, two-stage stochastic programming is recognized as a powerful method for tackling random variables with known probability distributions. In a typical two-stage stochastic programming, a decision is made in the first stage only when the distributional information on random variables is available. A second-stage decision or recourse decision can then be taken after a random event occurs. Such a method is suitable for dealing with the flood control problem in a two-stage fashion (Birge & Louveaux, 1988). For example, decision makers can determine an allowable flood diversion level according to the existing capacity of the floodplain before the flood season, and then they may want to carry out a corrective action when a flood occurs. Chance-constrained programming is another alternative for solving optimization problems that involve random uncertainties and supporting risk-based decision making (Charnes & Cooper, 1959). In chance-constrained programming, one or more sets of constraints are allowed to be violated with a specified probability since a solution that satisfies all possible outcomes can be prohibitively expensive. For the planning of flood control systems, allowing certain constraints to be violated with a low probability can be a reasonable and practical strategy for providing an in-depth analysis of trade-offs between economic outcomes and associated risks. Thus, an integration of two-stage stochastic programming and chance-constrained programming is necessary to support flood control planning and operations studies by taking into account randomness in different ways (Wang & Huang, 2014b).

In flood control problems, the related economic data, such as regular costs of flood diversion and capital costs of floodplain expansions, commonly act as the coefficients of the objective function in a cost minimization model. They are often given as probability distributions obtained from the estimates of a group of decision makers or stakeholders, which play a crucial role in the decision-making process. It is thus indispensable to address randomness in the coefficients of the objective function. The fractile criterion optimization model or Kataoka's model is then introduced to deal with random coefficients by using statistical features (Geoffrion, 1967; Kataoka, 1963). In fact, the probabilistic objective function interacts with chance constraints in the decision process, and their correlations may have significant effects on the model output. To conduct a systematic analysis of random uncertainties, it is also desired to explore potential interactions between the probabilistic objective function and chance constraints.

Therefore, the objective of this study is to develop a risk-based factorial probabilistic inference method for addressing stochastic objective function and constraints as well as their interactions in a systematic manner. Statistical significance for each of the linear, nonlinear, and interaction effects of risk parameters involved in stochastic programming will be uncovered through performing a multi-level factorial analysis. The proposed methodology will be applied to a case study of flood control to demonstrate its validity and applicability, and will also be compared with the fractile criterion optimization model and the chance-constrained programming technique, respectively.

2. Methodology

2.1. Two-stage stochastic programming with chance constraints

In a two-stage stochastic programming model, two types of decision variables can be distinguished: first-stage and second-stage variables. The first-stage decisions are made in the face of uncertainty. Once a random event occurs, the second-stage decisions or recourse actions can be taken in case of infeasibility caused by the first-stage decisions. A typical two-stage stochastic programming model can be formulated as (Birge & Louveaux, 1988):

$$\text{Min } f = C^T X + E[Q(X, \omega)] \tag{1a}$$

subject to:

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

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

with

$$Q(X, \omega) = \min D(\omega)^T Y \tag{1d}$$

subject to:

$$T(\omega)X + W(\omega)Y \le H(\omega) \tag{1e}$$

$$Y \ge 0 \tag{1f}$$

where $C \in R^{n_1}$, $X \in R^{n_1}$ (a vector of first-stage decision variables), $A \in R^{m_1 \times n_1}$, $B \in R^{m_1}$, $D \in R^{n_2}$, $Y \in R^{n_2}$ (a vector of second-stage decision variables), $T \in R^{m_2 \times n_1}$, $W \in R^{m_2 \times n_2}$, $H \in R^{m_2}$, ω is a random vector, and ω (D, T, W, H) contains the data of the second-stage problem. In the flood control problem, the first-stage decision variable represents the amount of allowable flood flows diverted to each floodplain, while the second-stage decision variable represents the amount of excess flood diversion when a random flood event occurs with a given probability. The objective of this problem is to minimize the total system cost subject to several constraints that restrict the total amount of allowable and excess flood diversion within the existing diversion capacity for each floodplain. Letting the random vector ω take a finite number of possible realizations $\omega_1, \ldots, \omega_k$ with respective probability of occurrence $p_1, \ldots, p_k$, $\sum p_k = 1$, the above problem can be written as a deterministic equivalent linear program:

$$\text{Min} f = C^T X + \sum_{k=1}^{m} p_k D^T Y \tag{2a}$$

subject to:

$$AX \le B \tag{2b}$$

$$TX + WY \le \omega_k, \quad k = 1, 2, \ldots, m \tag{2c}$$

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

$$Y \ge 0 \tag{2e}$$

Two-stage stochastic programming reflects the dynamic nature of decision problems through constructing a set of scenarios that represent the realizations of random variables. As an alternative method of stochastic optimization, chance-constrained programming is recognized as a powerful technique for dealing with probabilistic constraints. This method was first introduced by Charnes and Cooper (1959). The main feature of chance-constrained programming is that certain constraints are allowed to be violated with a specified probability and the resulting solutions ensure the probability of complying with constraints, which can thus be used to quantify the relationship between the objective-function value and the constraint-violation risk. A typical chance-constrained programming model can be formulated as:

$$\text{Min } f = C^T X \tag{3a}$$

subject to:

$$\Pr[\{\omega | A(\omega)X \le b(\omega)\}] \ge 1 - \alpha, \tag{3b}$$

$$X \ge 0, \tag{3c}$$