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Reliability-oriented multi-objective optimal decision-making approach for uncertainty-based watershed load reduction

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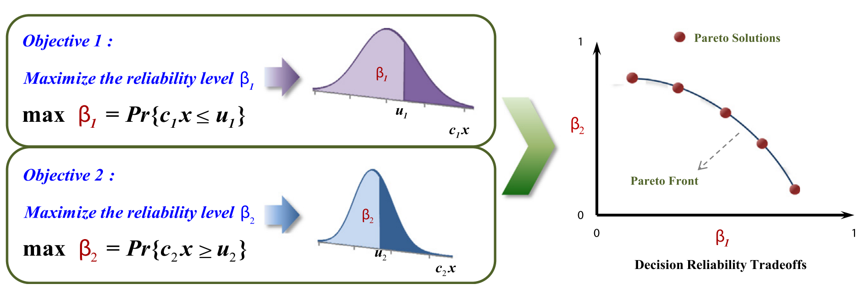
HIGHLIGHTS

- Reliability-oriented multi-objective (ROMO) optimal decision approach was proposed.
- The approach can avoid specifying reliability levels prior to optimization modeling.
- Multiple reliability objectives can be systematically balanced using Pareto fronts.
- Neural network model was used to balance tradeoff between reliability and solutions.

GRAPHICAL ABSTRACT



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ABSTRACT

Water quality management and load reduction are subject to inherent uncertainties in watershed systems and competing decision objectives. Therefore, optimal decision-making modeling in watershed load reduction is suffering due to the following challenges: (a) it is difficult to obtain absolutely "optimal" solutions, and (b) decision schemes may be vulnerable to failure. The probability that solutions are feasible under uncertainties is defined as reliability. A reliability-oriented multi-objective (ROMO) decision-making approach was proposed in this study for optimal decision making with stochastic parameters and multiple decision reliability objectives. Lake Dianchi, one of the three most eutrophic lakes in China, was examined as a case study for optimal watershed nutrient load reduction to restore lake water quality. This study aimed to maximize reliability levels from considerations of cost and load reductions. The Pareto solutions of the ROMO optimization model were generated with the multi-objective evolutionary algorithm, demonstrating schemes representing different biases towards reliability. The Pareto fronts of six maximum allowable emission (MAE) scenarios were obtained, which indicated that decisions may be unreliable under unpractical load reduction requirements. A decision scheme identification process was conducted using the back propagation neural network (BPNN) method to provide a shortcut for identifying schemes at specific reliability levels for decision makers. The model results indicated that the ROMO approach can offer decision makers great insights into reliability tradeoffs and can thus help them to avoid ineffective decisions.

1. Introduction

The deterioration of surface water bodies has been a global concern since the 1980s, challenging environmental decision makers and stakeholders. Scientists have demonstrated that nutrient enrichment is one

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of the main causes of lake and estuarine eutrophication (Seehausen et al., 1997; Huisman et al., 2005; Hautier et al., 2009; Shen et al., 2014). It is thereby necessary to implement nutrient load reduction programs to improve water quality and restore aquatic ecological health (Diaz and Rosenberg, 2008; Faulkner, 2008; Conley et al., 2009). Alternative strategies for load reduction should be organized effectively and efficiently at the watershed scale (Kramer et al., 2006), in which the optimization models can assist the decision-making process by proposing economically effective decision schemes and determining the optimal arrangements of alternative measures (Zou et al., 2010; Cao et al., 2010; Sadegh and Kerachian, 2011). The traditional deterministic optimal decision is based on the assumption of fully recognized systems and states. However, the decision-making process on nutrient load reduction is inevitably complicated by uncertainties, including (a) uncertain parameters, (b) competing and ambiguous decision objectives, and (c) deviations in judgment of stakeholders (Beck, 1987; Refsgaard et al., 2007; Tavakoli et al., 2014). Neglecting or incorrectly estimating uncertainties will result in ineffective and misleading decisions. Uncertainty analysis in environmental decision making has triggered much attention, and various methods have been developed to represent and handle uncertainty information in optimization models for reliable decisions (Zhang et al., 2009; Wang et al., 2012; Housh et al., 2013).

In modeling, uncertain parameters are usually quantitatively represented as stochastic distributions (Wagner and Gorelick, 1987; He et al., 2006; Qin et al., 2007; Bastin et al., 2013). Stochastic mathematical programming (SMP) is a widely used method for optimal decision making in stochastic systems. It has been applied to handling probabilistic parameters for decades (Stedinger et al., 1984; Shea and Possingham, 2000; Santoso et al., 2005; Pena-Haro et al., 2011), among which chance constrained programming (CCP) developed by Charnes and Cooper (1959) is the most commonly used (Sniedovich and Davis, 1975; Xie et al., 2011; van Ackooij et al., 2014). For optimal decision making on water quality management, some strict constraints for implementing load reduction plans will always exist, such as limited public budget and total environmental capacity (TEC). In traditional deterministic optimization models, the restrictions of available resources of budget and environmental capacity are represented as constraint functions. In CCP models, the probability that the decision scheme is feasible with the limitation of resources is analyzed and defined as the decision reliability (Morgan et al., 1993). CCP models have shown great potential in assisting decision making on practical optimal water quality management under randomness (Huang, 1998; Wang et al., 2004; Gren, 2008). For CCP models, however, there are some limitations for its decision application, including (a) the reliability aspirations of the decision makers that must be prescribed, and (b) schemes at various reliability levels that require multiple runs of the optimal solution algorithm (He et al., 2008; Xie et al., 2011). There will be many difficulties in determining the reliability levels without available information on the relevant decision performances.

Decisions should be made based on a tradeoff analysis between reliability levels and system performance, such as cost-risk tradeoffs for the arrangement of load reduction strategies. In previous studies, a tradeoff analysis was usually realized by testing a series of different reliability scenarios (Liu et al., 2008; Roy et al., 2010; Rasekh et al., 2010). For each scenario, the reliability levels of various constraints were assigned with a unified value, and the diversity of the reliability levels of the constraints is not considered. Decision makers may possess diverse reliability preferences towards different constraints. To depict the diversity among constraints, Dong et al. (2014) applied the Taguchi method to design multiple preference scenarios. However, all possible combinations of reliability levels cannot be enumerated exhaustively. The choice space of the decision makers is limited because only a few scenarios were provided in previous studies. Multiple reliability scenarios also require solving CCP models repeatedly, resulting in low decision efficiency.

To overcome the above limitations of CCP, a reliability-oriented multi-objective (ROMO) optimal decision-making approach was proposed in this study. The probability of achieving particular goals under a random environment (i.e., decision reliability) was established as an optimization objective. It was achieved in two steps through (a) ROMO optimization modeling and (b) scheme identification. Because various criteria may be considered to judge decision performance in practice, ROMO optimization models involve objectives for maximizing different aspects of decision reliability. In this study, the models were solved by the controlled elitist non-dominated sorting genetic algorithm (CE-NSGA-II), an advanced multi-objective evolutionary algorithm (MOEA). Scheme identification, which was achieved by artificial neural networks (ANNs), was implemented to reveal the quantitative relationship between decision reliability and implementation schemes. The ROMO approach provides a shortcut for accessing decision variables at expected reliability levels and contributes to deducing other alternative schemes in addition to a limited number of CE-NSGA-II solutions. Using the reliability-oriented approach developed in this study, all of the available schemes, reflecting diverse reliability preferences, can be assessed by one single run of the optimal solution algorithm. This reflects the intention of decision makers to maximize the feasibility of the decision and thus avoid predefinition of the aspirations for reliability levels. The ROMO approach was applied for decision making on watershed nutrient load reduction in Lake Dianchi, one of the three most eutrophic lakes in China, to provide effective support for decision making under uncertainties and two competing reliability objectives.

2. Materials and methods

2.1. Reliability-oriented optimization model

A typical CCP model can be formulated as follows (Charnes and Cooper, 1963):

$$\text{Max } f(\boldsymbol{w},\boldsymbol{x}) \tag{1}$$

subject to:

$$Pr\left\{\tilde{g}_j\left(\tilde{\boldsymbol{w}}_j,\boldsymbol{x}\right)\le b_j\right\}\ge\beta_j, j=1,2,\ldots,k \tag{2}$$

$$\boldsymbol{x}\in D \tag{3}$$

where $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$ is an n-dimensional vector of decision variables; D is a deterministic convex set, restricting the feasible region of $\boldsymbol{x}$. $f(\boldsymbol{w}, \boldsymbol{x})$ is the objective function, which is aimed to be maximized under the constraint formulated as Eqs. (2) and (3); $\boldsymbol{w} = (w_1, w_2, \ldots, w_n)$ is the deterministic parameter vector for the objective function; $\tilde{g}_j\left(\tilde{\boldsymbol{w}}_j,\boldsymbol{x}\right)$ is the constraint functions with stochastic parameters; $\tilde{\boldsymbol{w}}_j=\left(\tilde{w}_{1,j},\tilde{w}_{2,j},\ldots,\tilde{w}_{n,j}\right)$ is the stochastic coefficient vector for the jth constraint function; b_j is the allowable maximum value of the corresponding constraint function; $Pr\left\{\tilde{g}_j\left(\tilde{\boldsymbol{w}}_j,\boldsymbol{x}\right)\le b_j\right\}$ denotes the probability of respecting the inequality $\tilde{g}_j\left(\tilde{\boldsymbol{w}}_j,\boldsymbol{x}\right)\le b_j$ inside the braces; and $\beta_j(0 \le \beta_j \le 1)$ is the reliability level, which limits the minimum value of $Pr\left\{\tilde{g}_j\left(\tilde{\boldsymbol{w}}_j,\boldsymbol{x}\right)\le b_j\right\}$. In this paper, stochastic coefficients or functions are labeled with tildes to indicate their involvement with uncertainties.

CCP models are limited by prescribed reliability levels. Decision makers are required to determine the reliability levels β_j before solving by CCP. It is a common practice to assign β_j with a unified value $R(0\le R\le 1)$, and the constraints of Eq. (2) were then transformed into:

$$Pr\left\{\tilde{g}_j\left(\tilde{\boldsymbol{w}}_j,\boldsymbol{x}\right)\le b_j\right\}\ge R, j=1,2,\ldots,k. \tag{4}$$