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Test application of Bayesian Programming: Adaptive water quality management under uncertainty

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Abstract

A new method, Bayesian Programming (BP), developed by Harrison [Harrison KW. Multi-stage decision-making under uncertainty and stochasticity: Bayesian Programming. Adv Water Resour, submitted for publication] is tested on a case study involving optimal adaptive management of a river basin. The case study considers anew the process of permitting pulp mills on the Athabasca River in Alberta, Canada. The problem has characteristics common to many environmental management problems. There is uncertainty in the water quality response to pollutant loadings that will not be completely resolved with monitoring and the resolution of this uncertainty is impeded by the stochastic behavior of the water quality system. A two-stage adaptive management process is optimized with BP. Based on monitoring data collected after implementation of the first-stage decision, the uncertainties are updated prior to the second decision stage using Bayesian analysis. The worth of this two-stage adaptive management approach to this problem and the worth of monitoring are evaluated. Conclusions are drawn on the general practicality of BP for adaptive management. Potential strategies are outlined for extending the BP approach to secure further benefits of adaptive management.

Keywords: Decision-making under uncertainty; Stochastic modeling; Markov chain Monte Carlo; Mathematical programming; Streeter–Phelps water quality model

1. Introduction

Harrison [10] developed a new mathematical programming-based method for decision-making under uncertainty, Bayesian Programming (BP), and demonstrated the problem for a small illustrative problem. The primary purpose of this paper is to demonstrate the practical application of BP for a more complex and realistic environmental management problem. A problem of adaptive management is considered, as substantial attention in the field of water quality management has recently focused on adaptive management, and as BP is well suited for this problem. Specifically, a river basin management problem is selected, as the general problem of river basin management has served as a test-bed for new mathematical programming-based techniques (e.g., [24,19]).

The National Research Council [17] report on a water quality management program (the TMDL program) advocated an adaptive approach to water quality management. An adaptive approach treats water quality management as a sequential decision-making process, where the outcomes of management decisions are carefully monitored. The rationale for adaptive management is that a one-time fix to a water quality problem will likely fail due to the inability to predict accurately the outcomes of alternative management actions due to scientific uncertainty regarding water quality systems [28]. Instead, an incremental approach may be best, where the outcomes of management strategies are carefully monitored and adapted over time as the system response is better understood. Importantly, each proposed management decision is viewed as an experiment.

The incorporation of Bayesian statistical analysis within adaptive management frameworks was advocated in the National Research Council [17] report due to its ability to integrate modeling and monitoring information.

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Bayesian analysis has also been advocated by others, e.g., by Hobbs [11] for water resources management. It is central to the BP approach. Prato [20] discusses the role that Bayesian analysis can play in the adaptive management of ecosystems, comparing its strengths over frequentist approaches, through a small example involving one binary decision variable and one binary uncertain variable. However, systematic search methods, e.g., mathematical programming solution procedures, and other methods are needed to address the "curse of dimensionality" that arises when extending the problem to more complex applications.

Mathematical programming has been applied to the management of water quality under uncertainty. However, the previous applications reported have almost exclusively assumed the decision process to be non-adaptive. Burn and McBean [1] and Takyi and Lence [24], for example, examine one-stage decision-making under uncertainty and stochasticity, using chance-constrained programming formulations. Both of these studies consider sources of uncertainty and stochasticity similar to those considered here, including uncertainties related to streamflows and reaction rates. For tractability, Burn and McBean utilize first-order uncertainty analysis, a technique that is also used in this study for the stochastic modeling. Takyi and Lence, for computational efficiency, applied Monte Carlo for uncertainty propagation, and optimization for decision search, strategies that BP also incorporates. However, as they assumed a non-adaptive approach, the experimental value of the pollution control decision and possibility for a recourse decision after monitoring of the decision were not incorporated into the decision search. In contrast, BP incorporates the experimental value of the decisions within an optimal multiple-stage framework; uncertainties are continually resolved (with a Markov chain Monte Carlo (MCMC) implementation of Bayesian analysis) as monitoring data is collected and decisions are adjusted accordingly.

This paper makes two contributions. Previously, BP has been demonstrated for an illustrative problem [10]. Here, BP is demonstrated for a realistic case study, the optimal adaptive management of a river basin. The second contribution is the investigation into the value of adaptive management for the case study under consideration. Here, the simplest adaptive management implementation, two-stage adaptive management is considered. The adaptive management solutions identified with BP are compared to optimal non-adaptive solutions in which a single decision stage is assumed. Also, optimal adaptive management is compared to "myopic" adaptive management where the outcome of the non-adaptive solution (found through analysis that "sees" only a single stage) is monitored and can be adjusted after uncertainty updating. Answers to the following specific questions are sought in the case study:

- How would the river basin be managed differently with an adaptive approach?
- What is the increase in gains achievable with an adaptive approach?
- What is the worth of monitoring?
- What are the gains of a "myopic" adaptive approach?
- Can BP be demonstrated for a realistic problem?

The organization of the paper is as follows. An overview of BP is presented in Section 2—more details are provided by Harrison [10]. In Section 3, BP is applied to the case study to identify the optimal two-stage adaptive approach. After describing in Section 4 the modeling of alternative approaches (non-adaptive and myopic adaptive), the results are presented and discussed (Section 5). Finally, possible directions for further research to enhance the benefits of adaptive management are provided in Section 6.

2. Bayesian Programming

The development of BP was motivated by the desire to solve problems of the kind investigated in the case study (Section 3) and illustrated in the influence diagram of Fig. 1 [10]. Represented in Fig. 1 are characteristics that are common to many environmental management problems: uncertain, unobservable parameters θ that affect observable quantities y^1, stochastic elements that affect y^1 (conveyed by representation of y^1 as a chance variable), and multiple decision stages, here two decision stages (x^1 and x^2). The decision and chance outcomes all affect the result node ("Cost"). (According to convention, though, only the arrow to the result node from the final in a series of sequential decisions is shown to prevent clutter; all though are assumed to affect the result node.) BP was developed for the case in which x^1 and x^2 are combinatorial decisions. BP allows for the assessment of whether, given the uncertainties and monitoring, consideration of the follow-up decision x^2 should alter the initial decision x^1 if cost is to be minimized. BP also can accommodate a more general problem, for example, in which y^2 is not conditionally independent of y^1.

In mathematical programming form, the optimization problem, given two decision stages, is a nested problem:

$$\min_{x^1} \int_{y^1} p(y^1;x^1) \times \left[\min_{x^2} \int_{\theta,y^2} p(\theta,y^2|y^1;x^1,x^2)c(x^1,x^2,y^1,y^2,\theta)\mathrm{d}\theta\,\mathrm{d}y^2\right]\mathrm{d}y^1 \tag{1}$$

The objective is to find the value of x^1 that minimizes the expected cost (or more generally, maximizes expected utility), assuming also that the expected costs of the second-stage decision will be minimized. The function $c(x^1,x^2,y^1,y^2,\theta)$ indicates the costs associated with the implementation of x^1 and x^2, observation of y^1 and y^2, and underlying true θ. In Eq. (1), it is assumed that any constraints that might exist are incorporated into the objective function with penalty functions. The notation, e.g, $p(a|b;c)$, is meant to convey "the probability of a given b and given the value of the quantity c"; the notation is used