Journal of Environmental Management 77 (2005) 22–34

Journal of Environmental Management

www.elsevier.com/locate/jenvman

Policy planning under uncertainty: efficient starting populations for simulation-optimization methods applied to municipal solid waste management

Gordon H. Huang[a], Jonathan D. Linton[b], Julian Scott Yeomans[c,*], Reena Yoogalingam[d]

[a]Faculty of Engineering, University of Regina, Regina, SK S4S 0A2, Canada
[b]Lally School of Management, Rensselaer Polytechnic Institute, 110 8th Street, Troy, NY 12180, USA
[c]Management Science Area, Schulich School of Business, York University, Toronto, ON M3J 1P3 Canada
[d]Department of Management, Faculty of Business, Brock University, St. Catherines, ON L2S 3A1 Canada

Received 30 July 2004; revised 30 December 2004; accepted 14 February 2005
Available online 9 June 2005

Abstract

Evolutionary simulation-optimization (ESO) techniques can be adapted to model a wide variety of problem types in which system components are stochastic. Grey programming (GP) methods have been previously applied to numerous environmental planning problems containing uncertain information. In this paper, ESO is combined with GP for policy planning to create a hybrid solution approach named GESO. It can be shown that multiple policy alternatives meeting required system criteria, or modelling-to-generate-alternatives (MGA), can be quickly and efficiently created by applying GESO to this case data. The efficacy of GESO is illustrated using a municipal solid waste management case taken from the regional municipality of Hamilton-Wentworth in the Province of Ontario, Canada. The MGA capability of GESO is especially meaningful for large-scale real-world planning problems and the practicality of this procedure can easily be extended from MSW systems to many other planning applications containing significant sources of uncertainty.

Keywords: Public sector; Decision making; Uncertainty; Simulation; Evolutionary algorithms; Waste management; Planning; Modelling to generate alternatives

1. Introduction

In North America, the processing of municipal solid waste (MSW) represents a multibillion-dollar industry (Tchobanoglous et al., 1993, EPA 1988). Since MSW systems typically exhibit all of the characteristics generally associated with public planning, the field of MSW management has provided an ideal environment for the application of a wide variety of modelling techniques that have been used to support policy formulation (Linton et al., 2002). In public policy formulation, planners need to balance numerous competing factors prior to the determination of a final decision. Haynes (1981) and Wenger and Cruz-Uribe (1990) reviewed several mathematical programming techniques that have been used for integrating such factors into waste-management planning and numerous additional examples of optimization-based support methods that have been applied to MSW systems have been developed (Marks and Liebman, 1971; Walker, 1976; Hasit and Warner, 1981; Lund, 1990; Lund et al., 1994).

However, most optimization techniques are appropriate only for well-structured problems (Brown et al., 1974; Coyle, 1973; Liebman, 1975) and the multitude of uncertain components inherent within MSW systems render many deterministic optimization techniques unsuitable for MSW planning (Gottinger, 1986; MacDonald, 1996; Tchobanoglous et al., 1993). The major sources of uncertainty in an MSW system are due to the considerable dynamic and seasonal fluctuations in the quantities, types, and composition of the collected wastes. Difficulties in

* Corresponding author. Tel.: +1 416 736 5074; fax: +1 416 736 5687.
E-mail addresses: Huangg@uregina.ca (G.H. Huang), linton@rpi.edu (J.D. Linton), syeomans@schulich.yorku.ca (J.S. Yeomans), ryoogalingam@brocku.ca (R. Yoogalingam).

0301-4797/$ - see front matter © 2005 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jenvman.2005.02.008

planning for waste processing can be further compounded by significant stochastic uncertainties attributable to variations in waste density, humidity, temperature, waste-packing methods, and estimations of specific cost and revenue components. When input data cannot be expressed with appropriate certainty, the quality of any output produced by a deterministic optimization technique can be rendered highly questionable. As a result, simulation models have also been introduced into MSW management to circumvent several of the uncertainty shortcomings (Bodner et al., 1970; Baetz, 1990; Wang et al., 1994; Openshaw and Whitehead, 1985). Unfortunately, while Monte Carlo modelling permits an effective mechanism for comparing stochastic system performance, it does not provide a formal method for producing best system solutions.

To incorporate data uncertainty directly into optimal MSW solution creation, Huang et al. (1998, 2003) separately applied both grey programming (GP) and evolutionary simulation-optimization (ESO) to case study data from the Municipality of Hamilton-Wentworth. These studies focused upon the construction of an overall best operating policy for MSW management within the municipality, with the explicit goal being a 'function optimization' of the modelled system. The computationally efficient GP technique circumvents problems that other optimization approaches can encounter by processing system uncertainties as interval estimates (Huang et al., 1994a,b) and has been previously applied to various stochastic environmental planning problems (Bass et al., 1997; Chang and Wang, 1995; Chang et al., 1996; Huang, 1996; Huang et al., 1994a,b, 1995, 1996a,b, 1997; Yeh, 1996). In GP, problems containing interval parameters are transformed into a pair of deterministic submodels which, when solved in tandem, guarantee stable upper and lower limits for the solution. Unlike the more straightforward best-case/worst-case analysis, this transformation must be executed in a prescribed order using the output from the first submodel as direct input into the second submodel. The overall solution output from GP is a set of stable interval values both for the objective function and for all of the decision variables. Using GP, Huang et al. (1998) produced a plan for Hamilton-Wentworth's existing MSW system which reduced its maximum possible annual operating costs from $21 million to $20.8 million.

In contrast to GP, the ESO approach incorporates inherent stochastic parameters directly into its solution construction by representing all uncertainties as probability distributions in the model of the system (Fu, 2002; Kelly, 2002). While ESO holds considerable potential for application to a wide range of stochastic problems, the method cannot be considered a universally applicable, optimization panacea due to issues related to its solution effort. Because evolutionary search procedures are probabilistic processes, their actual solution times are stochastic, implying that search times can vary considerably from one implementation to another. As a result, one major difficulty experienced by ESO has been the length of time required for its solution search to converge to optimality, especially when applied to large-scale real-world problems (Lacksonen, 2001). Although the theoretical properties of ESO have been tested upon a rather limited spectrum of small test or 'toy' problems (Fu, 2002), the approach has not been applied to many 'real world' stochastic problems of practical size (Andradottir, 2002; Fu, 2002; Kelly, 2002). Accordingly, in a noteworthy assessment of ESO's 'real world' processing capabilities, Huang et al. (2003) optimized Hamilton-Wentworth's relatively large MSW problem using ESO and produced a plan that would never cost the municipality more than $20.6 million.

Usually optimization-based techniques only create single best solutions to problems. However, due to the presence of considerable system uncertainty and to the possibility that opposition from a key stakeholder could cause the outright elimination of an optimal solution from further consideration, policy makers faced with difficult and controversial choices generally prefer to be able to select from a set of alternatives (Huang et al., 1996b). From a policy formulation perspective, it can prove preferable to be able to generate several good alternatives that provide different approaches to the same problem. Preferably these alternatives would be relatively close to optimal when measured by their objective function values, but would differ significantly from each other in terms of the system structure as characterized by the values of their decision variables. In response to this solution option requirement, several methods for *modelling-to-generate-alternatives* (MGA) have been proposed (Baetz et al., 1990; Brill, 1979; Brill et al., 1981; Chang et al., 1980; Chang et al., 1982; Church and Huber, 1979; Falkenhausen, 1979; Gidley and Bari, 1986; Rubenstein-Montano and Zandi, 1999; Rubenstein-Montano et al., 2000). A drawback to these MGA approaches arises from the fact that they have all been based upon deterministic mathematical programming methods and consequently do not effectively incorporate system uncertainty directly into their solution construction.

Yeomans (2002) recently demonstrated that ESO, in addition to its function optimization capabilities, could also be used to generate multiple policy options that would never have been considered by decision-makers, while simultaneously integrating inherent uncertainty directly into each generated alternative. However, since the solution time of ESO impacts negatively on its ability to determine optimal solutions, this difficulty also extends into its use as an MGA procedure. While efforts have been made to accelerate solution convergence for evolutionary optimization in general (Goldberg, 1989; Reeves, 1993), no published examination has appeared for speeding up the performance quality of ESO procedures on 'real world' sized, stochastic applications (Fu, 2002).