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Water Resources Policy Formulation Using Simulation Optimization Combined with Fuzzy Interval Programming

[1]Julian Scott Yeomans and [2]Yavuz Gunalay
[1]Schulich School of Business, York University, OMIS Area, Toronto, ON, M3J 1P3, Canada
[2]Faculty of Business, Bahcesehir University, 34100 Besiktas Istanbul, Turkey

Abstract: Water resource policy formulation proves complicated because water management systems generally contain numerous sources of stochastic uncertainty. Simulation-Optimization (SO) methods, which incorporate system uncertainties using probability distributions, have been used for optimization in environmental planning. In this study, it will be shown that, in addition to function optimization, SO can be extended to formulate multiple policy alternatives meeting required system criteria-an approach referred to as Modelling to Generate Alternatives (MGA). Unfortunately, while SO holds considerable potential for application to a wide range of stochastic problems, its solution search times are, themselves, stochastic and vary considerably from one implementation to the next. Consequently, additional concurrent techniques will be presented to significantly reduce SO search times. The efficacy of this MGA approach for policy formulation is illustrated using a specific water resource management case study. Of significance is that, since SO techniques can be adapted to many disparate problems containing significant sources of uncertainty, the practicality of this approach can be extended to many other policy formulation applications, which contain stochastic system components.

Key words: Simulation-optimization, modelling to generate alternatives, interval programming, policy formulation, water resources planning

INTRODUCTION

Policy formulation problems involving water allocation have challenged water resource managers for decades. Water allocation becomes a controversial and conflict laden process when the competition between multiple water-users, such as municipal, industrial and agricultural sectors, intensifies. Recently, shrinking water supplies combined with increased population shifts have magnified this type of user competition. This competition can be expected to be further aggravated if the concern for water quantity and quality grows and if natural conditions become more unpredictable due to changing climatic conditions. Poorly planned systems for allocating water can produce serious problems under disadvantageous climate and river flow conditions. In previous eras, increasing water demand was met by developing new water sources. However, the significant economic and environmental costs associated with developing new water sources have made this approach unsustainable. This has led decision-makers to the point that unlimited expansion can no longer be the primary objective in water resources management. Instead, for optimum water resource allocation, it is more desirable to improve the existing water allocation and management systems in a more efficient, equitable and environmentally-benign manner by developing innovative environmental policy formulation techniques for water allocation under various complexities.

However, environmental policy formulation processes can prove to be exceedingly complicated, because the components of these systems generally contain significant degrees of stochastic uncertainty. This stochastic uncertainty renders most deterministic optimization solution methods relatively unsuitable for practical implementation. To incorporate data uncertainty into optimal environmental planning, two planning studies implemented the techniques of Simulation-Optimization (SO) (Yeomans *et al*., 2003) and Interval-Parameter Fuzzy 2-Stage Stochastic Programming (IPFTSP) (Maqsood *et al*., 2005). SO directly incorporates inherent system uncertainties expressed as probability distributions (Fu, 2002; Kelly, 2002), while IPFTSP provides a computationally efficient optimization

Corresponding Author: Julian Scott Yeomans, Schulich School of Business, York University, OMIS Area, Toronto, ON, M3J 1P3, Canada

technique in which system uncertainties can be represented by interval estimates (Huang *et al*., 1994a, 1994b, 1998).

Because its search procedures involve probabilistic processes, a major difficulty experienced by SO is the length of time required for its solution search to converge to optimality (Lacksonen, 2001). While, optimization-based techniques can generally only create single best solutions to problems, from an environmental policy formulation perspective it is often preferable to generate several alternatives that provide multiple different perspectives to the same problem. Preferably, these alternatives would possess near-optimal objective measures, but would differ from each other in terms of the system structures characterized by their decision variables. In response to this option-generation requirement, several approaches collectively referred to as Modelling to Generate Alternatives (MGA) have been developed (Baetz *et al*., 1990; Brill *et al*., 1982; Chang *et al*., 1982; Gidley and Bari, 1986; Rubenstein-Montano *et al*., 2000). Policy makers, would then perform a subsequent comparison of these alternatives to determine, which option most closely satisfies their disparate goals and specific circumstances.

Yeomans (2002) demonstrated that SO could be used to generate multiple policy options that would never have been considered by decision-makers, while simultaneously integrating stoachastic system uncertainty directly into each generated alternative. Therefore, SO can be used to circumvent the naturally myopic design tendencies of policy-makers with a formal MGA mechanism for generating numerous policies that would not have been considered otherwise. Yeomans (2003) and Linton *et al*. (2002) have shown SO to be an effective MGA technique in environmental policy formulation. Unfortunately, other research has shown that the stochastic aspects of SO's solution time can severely and negatively impact its results and that the solution quality for any given problem can vary considerably from 1 implementation of SO to another (Fu, 2002; Kelly 2002; Lacksonen, 2001). Since, the solution time of SO impacts negatively on its ability to determine single optimal solutions, this difficulty clearly extends into its extension as an MGA procedure. Huang *et al*. (2005) and Yeomans (2007) have proposed different approaches to improve the search times and solution quality of SO. In an attempt to improve the SO process, these approaches are combined with the interval-parameter fuzzy 2-stage stochastic programming method (IFTSP) provided by Maqsood *et al*. (2005). In this study, it is illustrated how these approaches in combination with IFTSP impact the MGA capabilities of SO by using the water allocation case study presented in Maqsood *et al*. (2005).

EVOLUTIONARY SIMULATION-OPTIMIZATION FOR FUNCTION OPTIMIZATION

SO is comprised of a broadly defined set of solution approaches that combine simulation with some type of optimization method for stochastic optimization (Fu, 2002; Law and Kelton, 2000). In SO, all unknown objective functions, constraints and parameters are replaced by 1 or more discrete event simulation models in which the decision variables provide the settings under, which the simulation is performed. As simulation is computationally intensive, the optimization component is used to guide the solution search through the problem's feasible region using as few simulation runs as possible. One approach is to use an evolutionary algorithm as the optimization module. Evolutionary, SO maintains a population of candidate solutions throughout its execution and consists of 2 alternating phases; an evolutionary module and a simulation module. The evolutionary module considers the entire population of solutions during each generation of the search and evolves from the current population to a subsequent ane. Because of the system's stochastic components, all performance measures are necessarily statistics calculated from the responses generated in the simulation module. The quality (or fitness for survival) of each solution in the population is found by having its performance criterion, F, evaluated by simulation. After simulating each candidate solution, the respective fitness values are returned to the evolutionary module to be utilized in the creation of the next generation of candidate solutions. The fitness of each candidate solution within the population is ranked in comparison to every other candidate solution. These fitness measures are inputs to the evolutionary module where the next population of candidate solutions is created by an evolutionary algorithm. The evolutionary module evolves the system toward improved solutions in subsequent populations and ensures that the solution search does not become fixated at some local optima. After generating a new candidate solution set in the evolutionary module, the new population is returned to the simulation module for comparative evaluation. This alternating, 2-phase search process terminates when an appropriately defined stable system state has been attained.

MODELLING TO GENERATE ALTERNATIVES WITH SIMULATION OPTIMIZATION

SO provides a mechanism for generating multiple policy options that might never have been considered by decision-makers, while simultaneously integrating uncertainty directly into each generated alternative

(Yeomans, 2002). As described, evolutionary algorithms maintain a population of solutions throughout their searching phase. Each solution in a population corresponds to one specific policy option and, therefore, the population of candidate solutions represents an entire set of policy alternatives. When, evolving from ane population to a subsequent one, relatively weaker candidate solutions within a population become progressively replaced by better solutions in an evolutionary survival-of-the-fittest analogy (Holland, 1992). Therefore, upon completion of its search, SO's final resident population would necessarily correspond to a highly fit population. This final, fit population corresponds to a set of good policy alternatives that could be considered for actual implementation. Hence, SO actually formulates a collection of good solution alternatives for planning in addition to having determined its best solution and can therefore be considered a de facto MGA technique.

USING PENALTY FUNCTION MINIMIZATION TO IMPROVE SO

In SO, the feasibility of each candidate solution is assessed during the simulation analysis performed on the current population and, in hard-constrained optimization situations, any solution not satisfying the stated constraints has to be discarded. Gendreau (2002) has indicated that evolutionary algorithms, in general, (those that do not include a simulation component during their search) expend considerable computational effort in correcting the many infeasible or meaningless solutions that tend to be created by their evolutionary operators. However, incorporating infeasibilities via penalty functions reflecting degrees of constraint violation can rapidly force evolutionary searches toward more preferable solutions. For constrained deterministic optimization problems, Holland (1992) suggested implementing penalty-functions to reflect the degree of solution violation. Yeomans (2007) has shown how the penalty function approaches from discrete optimization can be extended into SO. Incorporating infeasible solutions into the search population via these penalty functions forces the evolutionary search to proceed toward more preferable feasible scenarios in order to reduce the negative impact from the penalties, while at the same time reducing the computational burden required in having to evaluate and discard infeasible instances.

USING INTERVAL PROGRAMMING TO IMPROVE SO

Because stochastic system problems contain many possible solutions, solution quality can be highly variable unless, an extensive search has been performed throughout the problem's entire feasible domain. Evolutionary methods are conducive to such extensive searches because the set of candidate solutions in their populations permit searches to be undertaken throughout multiple sections of the feasible region, concurrently. However, since evolutionary search procedures are probabilistic, the major difficulty experienced by SO has been the length of time required for it to converge to optimality (Fu, 2002; Lacksonen, 2001). SO searches commence from their initial population and then evolve from one population to subsequent ones. In general, initial populations have been randomly generated for numerous justifiable reasons (Holland, 1992). However, Reeves (1993) suggested that a directed generation of an initial population can sometimes prove more efficient than this traditional random approach in accelerating solution convergence. If a computationally efficient method exists to generate a good starting population, then this population can potentially direct solution searches into more preferable regions of a large feasible domain; thereby producing better solutions faster (Huang *et al*., 2005).

One computational technique is IFTSP, the interval-parameter fuzzy two-stage stochastic programming method that Maqsood *et al*. (2005) applied to water resources planning systems under uncertainty. The IFTSP model is derived by incorporating the concepts of interval-parameter and fuzzy programming techniques into a two-stage stochastic optimization framework. The IFTSP approach holds two advantages in comparison to other discrete optimization techniques that must incorporate stochastic uncertainties. Firstly, IFTSP enables the ability to reflect uncertainties expressed not only by possibility and probability distributions but also by discrete intervals. Secondly, IFTSP enables a linkage to be made with previously defined policies that must be respected, when analytical solution procedures are used. In the modeling formulation, penalties are imposed when policies expressed as targets are violated. In its solution algorithm, the IFTSP model is converted into two deterministic submodels, which correspond to the lower and upper bounds for the desired objective-function value. Interval solutions, which are stable in the given decision space with associated levels of system-failure risk, can then be obtained by solving the two submodels sequentially.

The developed models provide solutions that are expressed as stable interval solutions with different risk levels in the pre-established criteria. Because of its inherent efficiencies, it would be feasible for the IPFTSP described in Maqsood *et al*. (2005) to be used to rapidly generate this requisite good initial population from which to start SO (Huang *et al*., 2005).

FORMULATING ALTERNATIVES WATER RESOURCE POLICIES: CASE STUDY

As described above, it might prove possible to improve SO optimization by including penalty functions and initial population biasing. The case study of water resources management from Maqsood *et al*. (2005), will be used to directly illustrate how these function optimization improvements can be extended into. Obviously every solution difficulty encountered by SO in its function optimization role carries over when it is used as an MGA, policy formulation method. Huang and Loucks (2000) and Maqsood *et al.* (2005) examined a water resources management case study for allocating water in a dry season from an unregulated reservoir to 3 categories of users: a municipality, an industrial concern and an agricultural sector. The industrial concern and agricultural sector were undergoing significant expansion and needed to know how much water they could expect to receive. If insufficient water were available, they would need to curtail their expansion plans. If the promised water was delivered, it would contribute positive net benefits to the local economy per unit of water allocated. However, if the water was not delivered, the results would reduce the net benefits to the users. Included within these decisions was a determination of which one of the multiple possible pathways that the water would flow through in reaching the users. It was further possible to subdivide the various water streams with each resulting substream sent to a different user.

Since, cost differences from operating the facilities at different capacity levels produced economies of scale, decisions had to be made to determine how much water should be sent along each flow pathway to each user type. Therefore, any single policy option was composed of a combination of many decisions regarding which facilities received water and what quantities of water would be sent to each user type. All of these decisions were compounded by overriding system uncertainties regarding the seasonal water flows and their likelihoods.

Consequently, the case problem considered how to effectively allocate the water to the 3 user groups in order to achieve maximum net benefits under the elements of uncertainty present and how to incorporate water policies in terms of allowable amounts within this planning problem with the least risk for causing system disruption. Since, the uncertainties were expressed collectively as interval estimates, probability distributions and fuzzy membership functions and a link to a predefined policy was desired, Maqsood *et al*. (2005) improved upon the earlier solution in Huang and Loucks (2000) by solving this planning problem with their IFTSP approach. For the water resource system, a solution that would never produce a net benefit lower than \$2.02 million was constructed.

As described in earlier sections, optimizing this problem with SO required running the procedure to find the maximum system net benefit and the resulting terminal population provides the set of policy alternatives determined by SO in its capacity as an MGA procedure. To accelerate the search times and to improve solution quality, both penalty function minimization and IPFTSP were integrated into the process (Huang *et al*., 2005). This adaptation was accomplished with two modifications to the original model. Firstly, IPFTSP was used to generate the initial starting population and secondly, the original hard-constrained SO model was re-formulated to penalize any candidate solution lying outside the constraint limits. After incorporating these two modifications, six separate computational experiments were undertaken to compare the relative MGA performance of the reformulated penalty-function/IPFTSP SO to the original hard constrained-SO approach. Initial populations of size twenty were created by random generation for constrained-SO and by IPFTSP for the penalty-function procedure. Both procedures were run for fixed time intervals of 30 and 90 min. Recognizing that constrained-SO might expend considerable computational effort in creating and discarding infeasible solutions, a third time period was included that required the search to evolve through exactly fifty population generations. Each experimental setting corresponded to one specific combination of: the two different SO solution procedures and the three different time periods. A distinct set of policy options was generated for each of the 6 computational experiments. Upon termination, the entire surviving population would represent the set of 20 different policy options generated for water resources management within the region.

Table 1 contrasts the values of the net benefit objectives for each of the twenty policy options in the terminal populations under the six respective experimental settings performed. The lack of variability within each penalty constrained-SO column indicates that all solution benefits fall within similar ranges, indicating that these populations are comparatively equivalent from a net benefit standpoint. Conversely, a detailed examination of the resulting decision variables produced by penalty function/IPFTSP SO indicated that most of these options provided system structures that were quite distinct from each other. From a practical perspective, this finding demonstrates that penalty function/IPFTSP SO can generate considerably more higher benefit policy alternatives than the limited number of options that might be produced by a planner using an optimization

Table 1: Minimum system benefits ($ Millions) for the 20 solutions in terminal populations. Benefits have been sorted in non-increasing order

SO procedure:	Penalty function	Constrained SO	Penalty function	Constrained SO	Penalty function	Constrained SO
starting solution:	IPFTSP	random	IPFTSP	random	IPFTSP	random
solution time:	30 min	30 min	90 min	90 min	50 iterations	50 iterations
Solution number						
1	2.290	2.078	2.399	2.081	2.380	2.075
2	2.289	2.077	2.395	2.080	2.367	2.070
3	2.288	2.077	2.391	2.078	2.335	2.069
4	2.286	2.076	2.387	2.078	2.256	2.065
5	2.281	2.075	2.346	2.076	2.289	2.062
6	2.281	2.074	2.343	2.076	2.288	2.062
7	2.281	2.074	2.343	2.076	2.283	2.061
8	2.281	2.074	2.339	2.076	2.281	2.061
9	2.281	2.073	2.339	2.075	2.280	2.061
10	2.281	2.073	2.331	2.075	2.197	2.061
11	2.181	2.072	2.328	2.074	2.178	2.061
12	2.180	2.071	2.328	2.072	2.171	2.061
13	2.180	2.070	2.324	2.072	2.171	2.061
14	2.179	2.070	2.305	2.072	2.160	2.061
15	2.179	2.070	2.301	2.072	2.158	2.061
16	2.179	2.070	2.301	2.072	2.152	2.061
17	2.078	2.070	2.294	2.072	2.148	2.061
18	2.077	2.069	2.283	2.071	2.104	2.060
19	2.076	2.069	2.279	2.071	2.100	2.060
20	2.076	2.069	2.264	2.071	2.097	2.060

technique. Since, each alternative provides different water resource policies within the system, this leads to different utilizations of the various facilities in the region. In its MGA capacity, SO has produced 20 different policy alternatives possessing the requisite system characteristics with each option providing a different planning perspective. It should be noted that all 20 alternatives in each penalty function/IPFTSP setting have system benefits that are at least $70,000 higher than the existing municipal system. Because each alternative represents a distinct policy option of system utilization and every one of these options possesses a net benefit that is higher than the existing policy, this clearly indicates that SO has created an entire set of improved policies for water management in the region.

The constrained-SO columns in Table 1 show the solution alternatives created, when starting from randomly generated initial populations. In comparison to penalty function/IPFTSP, the constrained-SO populations exhibit considerably smaller variability in net benefits, representing a significantly less diverse set of policy options for the planners to choose from. The best net benefit of essentially all of the solutions found in these populations are lower than the worst solutions produced by the IPFTSP starting point and the lower benefit solutions are considerably lower. Therefore, it appears quite apparent that the general solution quality for the SO procedure beginning from a random initial population has deteriorated substantially in comparison to having the same procedure commence from a IPFTSP generated population. Evaluating the population characteristics from Table 1 from a search time perspective highlights certain other differentiating features between the SO approaches. For the 30 and 90 min search times, penalty-function/IPFTSP produced vastly superior populations than constrained-SO. While, the two populations generated by penalty-function/IPFTSP resemble each other in both time periods, in constrained-SO the 90 min search produced a superior population relative to the 30 min search. In the 50-generation experiment, penalty-function/IPFTSP produced a similar population to its 30 min trial. Most significantly, the 50 generation constrained-SO experiment demonstrated considerable solution improvement over its 30 and 90 min runs; providing alternatives that appear comparable in value to the penalty-function/IPFTSP solutions. However, an extremely important observation from the 50 generation experiments was that constrained SO required in excess of 3 h to iterate through its 50 generations, while penalty-function/IPFTSP took only 45 min. Hence, this experimentation reveals that longer solution searches in constrained SO produce markedly superior populations and that penalty-function/IPFTSP produces better populations than constrained SO in much shorter time spans.

Table 2 summarizes the single, best objective values obtained under the indicated settings. The table indicates that the constrained SO solutions improve with longer search times and that the 3 h, 50 generation experiment produced a solution within $300,000 of optimality. In stark contrast, all of the penalty function/IPFTSP experiments produced near optimal solutions with the 30 min and 50 generation runs within $100,000 of the best known solution and the 90 min trial achieving optimality. These

Table 2: Optimum net benefits (in millions of $) for the existing system

SO method and starting Condition employed	Solution search time 30 min	90 min	50 Iterations	24 h
Constrained SO and random starting solution	2.078	2.081	2.075	2.378
Penalty function SO and IPFTSP starting solution	2.290	2.399	2.380	N/A

findings confirm the search time benefits of penalty function/IPFTSP in that the 30 min trial produced a solution costing $200,000 more than the 3 h constrained-SO trial. Analogously to issues surrounding solution quality, it had been mentioned that the search times of evolutionary methods are stochastic. Commencing constrained SO from random starting points should produce solutions comparable to penalty-function/IPFTSP if longer search periods had been permitted. To illustrate this phenomenon, an additional 24 h, constrained SO experiment was performed and the last column of Table 2 shows the best solution found from this extended time experimentation. The solution demonstrates a dramatic value improvement, when contrasted against the earlier results and suggests that with extended search times, the best solutions found by constrained-SO do, indeed, become comparable to penalty-function/IPFTSP SO.

CONCLUSION

Environmental policy formulation is an extremely complicated process that can be impacted by a multitude of uncertain factors. Any ancillary techniques used to support policy generation must address all of these features and must be flexible enough to encapsulate the impacts from the inherent planning uncertainty. Concurrently, combining penalty function minimization together with IPFTSP improved SO's search time and solution quality, when solving stochastic problems. It was shown how SO could be used to efficiently formulate multiple near best policy alternatives for difficult, stochastic, environmental problems. Since, SO techniques can easily be adapted to a multitude of different types of stochastic problems, the practicality of this MGA approach can clearly be extended into many other environmental planning applications containing significant sources of uncertainty.

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