A Co-Evolutionary Simulation-Optimization Algorithm for Modelling to Generate Alternatives in Municipal Solid Waste Management Planning

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Abstract. Public sector decision-making typically involves complex problems that are riddled with competing performance objectives and possess design requirements which are difficult to quantify and capture at the time decision models are constructed. Environmental policy formulation can prove additionally complicated because the various system components often contain considerable stochastic uncertainty and frequently there are also numerous stakeholders holding incompatible perspectives. Consequently, there are invariably unmodelled performance design issues, not apparent at the time of the problem formulation, which can greatly impact the acceptability of any proposed solutions. While a mathematically optimal solution might provide the best solution to a modelled problem, normally this will not be the best solution to the real problem. Therefore, in public environmental policy formulation, it is generally preferable to be able to create several quantifiably good alternatives that provide very different approaches and perspectives to the problem. This study shows how simulation-optimization (SO) modelling can be combined into a co-evolutionary algorithm to efficiently generate multiple policy alternatives that satisfy required system performance criteria in highly uncertain environments and yet are maximally different in the decision space. The efficacy of this modelling-to-generate-alternatives approach is specifically demonstrated on a municipal solid waste management planning case.

Keywords: Modelling to generate alternatives, simulation-optimization, environmental decision making under uncertainty

1. Introduction

Public sector decision-making typically involves complex problems that are riddled with competing performance objectives and possess performance design requirements which are very difficult to capture at the time that any supporting decision models are constructed. Environmental policy formulation can prove even more complicated because the various system components often contain considerable degrees of stochastic uncertainty. Consequently, public sector environmental policy formulation often proves to be an extremely complicated and challenging process. While mathematically optimal solutions may provide the best results for the modelled problem, they are frequently not the best solution for the underlying real problem as there are invariably unmodelled issues and unquantified objectives not apparent at the time the
model was constructed. This is a familiar concern in public sector settings where final decisions tend to be shaped not only by quantified objectives, but also by stakeholder preferences and political/socio-economic objectives that are extremely subjective in nature. It is often not possible to express these subjective considerations clearly and, therefore, impossible to capture them quantitatively in any optimization model.

Consequently, from an environmental policy formulation standpoint it is often preferable to be able to generate several alternatives that provide multiple, disparate perspectives to the particular problem (Huang et al. 1996). Preferably these alternatives should all possess good (i.e. near-optimal) objective measures with respect to the modelled objective(s), but be fundamentally different from each other in terms of the system structures characterized by their decision variables. In response to this option creation requirement, several approaches collectively referred to as modelling-to-generate-alternatives (MGA) have been developed (Baetz et al. 1990; Baugh et al. 1997; Brill et al. 1981; Chang et al. 1982a, 1982b; Loughlin et al. 2001; Rubenstein-Montano & Zandi 1999; Rubenstein-Montano et al. 2000; Zechman & Ranjithan 2004). The primary motivation behind MGA is to produce a manageably small set of alternatives that are good with respect to modelled objectives yet as different as possible from each other in the decision space. In so doing, the resulting alternative solution set is likely to provide truly different choices that all perform somewhat similarly with respect to the modelled objectives, yet very differently with respect to the unmodelled issues.

Yeomans et al. (2003) showed how to incorporate data uncertainty directly into environmental planning using an approach referred to as simulation-optimization (SO). SO is a family of optimization techniques that incorporates inherent system uncertainties expressed as probability distributions into its computational procedure (Fu 2002). Linton et al. (2002) and Yeomans (2008) have shown that SO can be considered an effective, though very computationally intensive, MGA technique for environmental policy formulation. However, none of these SO MGA approaches have been able to provide guarantees to ensure that the created alternatives are sufficiently different in decision variable structure from one another.

In this paper, it is shown how to efficiently generate maximally different solution alternatives for public environmental policy planning situations containing considerable stochastic uncertainty by using a version of the technique of Zechman & Ranjithan (2004) that has been specifically modified for implementation with SO. This new stochastic approach is very computationally efficient, since it permits the generation of multiple, good solution alternatives in only a single computational run of the SO algorithm rather than the multiple implementations required in most deterministic MGA procedures. This study illustrates the efficacy of the MGA capabilities of this new SO procedure by testing it on the municipal solid waste (MSW) management planning study taken from Yeomans et al. (2003).

2. Simulation-Optimization for Function Optimization

Determining optimal solutions to large stochastic problems proves to be very complicated when system uncertainties have to be accounted for and incorporated directly into the solution procedure (Fu 2002). When stochastic conditions exist, values for the constraints and objectives can only ever be efficiently estimated by simulation. SO is a broadly defined family of solution approaches that combines simulation with some type of optimization method for stochastic optimization (Fu 1994, 2002). In SO, all unknown objective functions, constraints, and
parameters are replaced by one or more discrete event simulation models in which the decision variables provide the settings under which the simulation is performed. Since all measures of system performance are stochastic, any potential solution, $X$, needs to be evaluated via simulation. As simulation is computationally intensive, an optimization component is used to guide the search for solutions through the problem’s feasible region using as few simulation runs as necessary. Evolutionary methods are conducive to these extensive searches because the complete set of candidate solutions maintained in their population permits concurrent searches to be undertaken throughout multiple sections of the feasible region.

Evolutionary SO consists of two alternating computational phases; (i) an evolutionary module and (ii) a simulation module. Evolutionary SO maintains a set, or “population”, of candidate solutions throughout its execution. The quality or “fitness” of each solution in this population is found by having its performance criterion, $F$, evaluated by simulation. After simulating each candidate solution, the respective fitness values become inputs to the evolutionary module for the creation of the next generation of solutions. The fitness of each solution within the population is ranked in comparison to every other candidate solution. These ranked fitness measures are the inputs to the evolutionary module where the next solution population is created using the evolutionary algorithm. The driving force underlying evolutionary procedures is that fitter solutions in a current population possess a greater likelihood for survival and progression into the subsequent generations. After generating a new candidate solution set, the evolutionary module returns the new population to the simulation module for comparative evaluation. This alternating, two-phase search process terminates when an appropriately stable system state has been attained (Yeomans 2008). The optimal solution produced by the procedure is the single best solution found over the course of the entire search.

3. Modelling to Generate Policy Alternatives with Simulation-Optimization

In public policy determination, there are always numerous system objectives and requirements that are never explicitly included or apparent in the decision formulation stage. Moreover, it may never be possible to explicitly express all of the subjective considerations in environmental public policy formulation because there are generally numerous incompatible, competing, adversarial stakeholder groups. Therefore these subjective aspects remain unquantified and unmodelled in the construction of any corresponding decision models. This is a common occurrence in situations where the final decisions are constructed based not only upon clearly stated and modelled objectives, but also upon environmental, political and socio-economic goals and stakeholder preferences that are fundamentally subjective (Baugh et al. 1997; Brill et al. 1981; Zechman & Ranjithan 2004).

To illustrate the implications of an unmodelled objective on a decision process, assume that the optimal solution for a quantified, single-objective, maximization decision problem is $X^*$ with corresponding objective value $Z^*$. Now suppose that there exists a second, unmodelled, maximization objective $Z_2$ that reflects environmental/political acceptability. Let the solution $X^N$, belonging to the noninferior, 2-objective set, represent a potential best compromise solution if both objectives could somehow have been simultaneously evaluated by the decision-maker. While $X^*$ might be viewed as the best compromise solution to the real problem, it would clearly appear inferior to the solution $X^*$ in the quantified model since it must be the case that $Z^N \leq Z^*$. This observation implies that when unmodelled objectives are factored into decision
making processes, mathematically inferior solutions for the modelled problem can potentially be optimal for the real problem. Therefore, when unmodelled objectives and unquantified issues exist, different approaches are required in order to not only search the decision space for the noninferior set of solutions, but also to explore the decision space for inferior alternative solutions to the modelled problem.

In the remainder of this section, an MGA procedure that is capable of incorporating uncertainty directly into its generated alternatives via SO is developed using a modified adaptation of Zechman & Ranjithan (2004). In order to properly motivate this procedure, it is necessary to provide a more formal definition of the goals of an MGA process (Brill et al. 1981; Zechman & Ranjithan 2004). Suppose the optimal solution to an original mathematical model is $X^*$ with objective value $Z^* = F(X^*)$. The following model can then be solved to generate an alternative solution that is maximally different from $X^*$:

$$\text{Max} \quad \Delta = \sum_i |X_i - X_i^*|$$

s.t.

$$X \in D$$

$$|F(X) - Z^*| \leq T$$

where $\Delta$ is a difference function and $T$ is a target specified in relation to the original optimal function value $Z^*$. $T$ is a user-supplied value that represents how much of the inferior region is to be explored for alternative solutions.

The new MGA procedure is designed to generate a small number of good but maximally different alternatives and is based upon the concept of co-evolution. In this algorithm, stratified subpopulations within the evolutionary algorithm’s overall population are established to collectively evolve toward different alternative solutions. Each desired solution alternative is represented by one subpopulation that undergoes the common evolutionary search procedure. This search can be structured based upon any standard evolutionary search procedure containing appropriate encodings and operators that best suit the problem being solved. The survival of solutions in each subpopulation depends upon how well the solutions perform with respect to the modelled objective(s) and by how far away they are from all of the other solutions in the decision space. Thus, the evolution of solutions in each subpopulation is influenced by those solutions contained in the other subpopulations, forcing the evolution of each subpopulation towards good but distant regions of the decision space.

The main steps within the co-evolutionary procedure are as follows:

1. Create an initial population with $P$ subpopulations. The value for $P$ must be established a priori by decision-maker and $P$ represents the desired number of alternative solutions to be generated. $S_p$ represents the $p^{th}$ subpopulation, $p = 1, \ldots, P$ and there are $K$ solutions contained within each $S_p$. $S_i$ is dedicated to the search for the overall optimal solution to the modelled problem. The solution from $S_i$ will be used to establish the benchmarks for the relaxation constraint.

2. Evaluate the set of solutions in $S_i$ using simulation and identify the best solution with respect to the modelled objective.

3. In $S_p$, $p = 2, \ldots, P$, evaluate all solutions with respect to the modelled objective using the simulation module. Solutions meeting the target constraint are designated feasible, while all others are designated as infeasible.
4. Apply an appropriate elitism operator to each $S_p$ to preserve the best individual in each subpopulation. In $S_i$, this is the best solution with respect to the modelled objective. In $S_p$, $p = 2, \ldots, P$, the best solution is the feasible solution most distant (the distance measure is defined in Step 7) in decision space from the other subpopulations. If all solutions in $S_p$ are infeasible, then this is the best individual solution with respect to the modelled objective.

5. Stop the algorithm if the termination criteria (such as maximum number of iterations or some measure of solution convergence) are met. Otherwise, proceed to Step 6.

6. Identify the decision space centroid, $C_{ip}$, for each of the $N$ decision variables $X_{ikp}$, $i = 1, \ldots, N$, in solution $k = 1, \ldots, K$, of $S_p$, $C_{ip} = (1/K) \sum_i X_{ikp}$. Alternatively, the centroid could be calculated as a fitness-weighted average.

7. For each solution $k = 1, \ldots, K$, in each $S_{iq}, q \neq 1$, calculate $D_{kj}$, a distance measure between that solution and all other subpopulations. $D_{kj} = \min \{ | X_{ikp} - C_{ip} | ; p = 2, \ldots, P, p \neq q \}$. This distance represents the minimum distance between solution $k$ in subpopulation $q$ and the centroids of all other subpopulations.

8. Apply a binary tournament to the solutions in each $S_p$. For $S_i$, the selection is with respect to the modelled objective. In each $S_{iq}, p \neq 1$, the selection is based on the fitness of the solution with respect to the modelled objective(s) as well as its distance from other subpopulations $D_{kp}$. For each $S_p, p \neq 1$, (i) when both solutions are feasible with respect to the relaxed constraint, select the one with the better objective, else (ii) if the majority of the solutions are feasible, select based upon the distance measure $D_{kp}$, otherwise, (iii) select based upon the objective function value.

9. In each $S_p$, apply recombination operators to the solutions selected in Step 8, and return to Step 2.

By adopting this co-evolutionary MGA methodology, multiple maximally different design options can be created that meet established system criteria, while simultaneously remaining acceptable and implementable in practice.

4. Case Study of SO used in MGA for Municipal Solid Waste Management Planning

The efficacy of this co-evolutionary SO MGA procedure will be illustrated using the municipal solid waste management planning study of Hamilton-Wentworth taken from Yeomans et al. (2003). Located at the Western-most edge of Lake Ontario, the Municipality of Hamilton-Wentworth covers an area of 1,100 square kilometers and includes six towns and cities. The Municipality is considered the industrial centre of Canada, although it simultaneously incorporates diverse areas of heavy industrial production with densely populated urban space, regions of significant suburban development, and large proportions of rural/agricultural environments. The MSW system within Hamilton-Wentworth must satisfy the waste disposal requirements of its half-million residents who, collectively, produce more than 300,000 tons of waste per year, with a budget of $22 million. The region had constructed a system to manage these wastes composed of: a waste-to-energy incinerator referred to as the Solid Waste Reduction Unit (or SWARU); a 550 acre landfill site; three waste transfer stations; a household recycling program; a household/hazardous waste depot, and; a backyard composting program. The three transfer stations have been strategically located to receive wastes from the disparate
municipal (and individual) sources and to subsequently transfer them to the waste management facilities for final disposal; either to SWARU for incineration or to the landfill. Wastes received at the transfer stations are compacted into large trucks prior to being hauled to the landfill site. These transfer stations provide many advantages in waste transportation and management; these include reducing traffic going to and from the landfill, providing an effective control mechanism for dumping at the landfill, offering an inspection area where wastes can be viewed and unacceptable materials removed, and contributing to a reduction of waste volume because of the compaction process. The SWARU incinerator burns up to 450 tons of waste per day and, by doing so, generates about 14 million kilowatt hours per year of electricity which can be either used within the plant itself or sold to the provincial electrical utility. SWARU also produces a residual waste ash which must subsequently be transported to the landfill for disposal.

Within this MSW system, decisions have to be made regarding whether waste materials would be recycled, landfilled or incinerated and additional determinations have to be made as to which specific facilities would process the discarded materials. Included within these decisions is a determination of which one of the multiple possible pathways that the waste would flow through in reaching the facilities. Conversely, specific pathways selected for waste material flows determine which facilities process the waste. It is possible to subdivide the various waste streams with each resulting substream sent to a different facility. Since cost differences from operating the facilities at different capacity levels produced economies of scale, decisions have to be made to determine how much waste should be sent along each flow pathway to each facility. Therefore, any single MSW planning option is composed of a combination of many decisions regarding which facilities received waste material and what quantities of waste are sent to each facility. All of these decisions are compounded by numerous overriding system uncertainties. Yeomans et al. (2003) ran an SO procedure for a 24-hour period to determine that the best for the existing system would never cost more than $20.6 million.

As outlined earlier, when public policy planners are faced with difficult and potentially controversial choices, they generally prefer to be able to select from a set of near-optimal alternatives that differ significantly from each other in terms of the system structures characterized by their decision variables. In order to create these alternative planning options, it would be possible to place extra target constraints into the original model which would force the generation of solutions that were different from their respective, initial optimal solutions. Suppose for example that ten additional planning alternative options were created through the inclusion of a technical constraint on the objective function that increased the total system cost of the original model from 1% up to 10% in increments of 1%. By adding these incremental target constraints to the original SO model and sequentially resolving the problem an additional 10 times, it would be possible to create the specific number of alternative policies desired for MSW expansion planning.

However, to improve upon the process of running ten separate instances of the computationally intensive SO algorithm to generate these solutions, the co-evolutionary MGA procedure described in the previous section was run only once, thereby producing the 10 additional maximally different alternatives shown in Table 1. Given the performance bounds established for the objective in each problem instance, the decision-makers can feel reassured by the stated performance for each of these options while also being aware that the perspectives provided by the set of dissimilar decision variable structures are as maximally different from each other as is feasibly possible. Hence, if there are stakeholders with incompatible standpoints holding diametrically opposing viewpoints, the policy-makers can perform an assessment of these
different options without being myopically constrained by a single overriding perspective based solely upon the objective value.

Table 1. Annual MSW Costs ($ Millions) for 11 Maximally Different Alternatives

<table>
<thead>
<tr>
<th>Best Solution</th>
<th>Overall</th>
<th>1%</th>
<th>2%</th>
<th>3%</th>
<th>4%</th>
<th>5%</th>
<th>6%</th>
<th>7%</th>
<th>8%</th>
<th>9%</th>
<th>1%</th>
<th>0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSW System Costs</td>
<td>20.6</td>
<td>20.9</td>
<td>20.9</td>
<td>21.1</td>
<td>21.4</td>
<td>21.4</td>
<td>21.8</td>
<td>22.0</td>
<td>22.2</td>
<td>22.3</td>
<td>22.5</td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, it should also be explicitly stated that these created alternatives do not differ from the lowest cost solution by at least the stated 1%, 2%, 3%, ..., 10%, respectively, but, in general, actually differ by less than these pre-specified upper deviation limits. This is because each of the best alternatives produced in $S_2$, $S_3$, ..., $S_{11}$, have solutions whose structural variables differ maximally from those of all of the other alternatives generated while simultaneously guaranteeing that their objective values deviate from the overall best objective by no more than 1%, 2%, ..., 10%, respectively.

Although a mathematically optimal solution may not provide the best approach to the real problem, it can be demonstrated that the co-evolutionary procedure does indeed produce very good solution values for any originally modelled optimization problem, itself. It should be explicitly noted that the cost of the overall best solution produced by the MGA procedure (i.e. the solution in $S_7$) is identical to the one found in the function optimization of Yeomans et al. (2003) – which is clearly not a coincidence. Expanding the population size in the SO procedure to include the subpopulations $S_2$, $S_3$, ..., $S_{11}$, does not detract from its evolutionary capabilities to find the best, function optimization solution in subpopulation $S_7$. Hence, in addition to its alternative generating capabilities, the MGA procedure simultaneously performs exceedingly well with respect to its role in function optimization.

As described earlier, public sector, environmental policy problems are typically riddled with incongruent performance requirements that contain significant stochastic uncertainty that are also very difficult to quantify. Consequently, it is preferable to create several quantifiably good alternatives that concurrently provide very different perspectives to the potentially unmodelled performance design issues during the policy formulation stage. The unique performance features captured within these dissimilar alternatives can result in very different system performance with respect to the unmodelled issues, thereby incorporating the unmodelled issues into the actual solution process. This example has demonstrated how co-evolutionary SO MGA modelling can be used to efficiently generate multiple, good policy alternatives that satisfy required system performance criteria according to prespecified bounds within highly uncertain environments and yet remain as maximally different from each other as possible in the decision space.

In totality, the results of this section underscore several important findings with respect to the use of SO within this co-evolutionary MGA procedure: (i) Co-evolutionary SO can be used to generate more good alternatives than planners would be able to create using other MGA approaches because of the evolving nature of its population-based solution searches; (ii) All of
the solutions produced by SO incorporate system uncertainties directly into their structure during their creation unlike all of the earlier deterministic MGA methods; (iii) The alternatives generated are good for planning purposes since their structures are all as maximally different from one another as possible (i.e. these differences are not just simply from the overall optimal solution); (iv) The MGA procedure is computationally very efficient since it need only be run once to generate its entire set of multiple, good solution alternatives (i.e. to generate \( n \) solution alternatives, MGA needs to run exactly the same number of times that SO would need to be run for function optimization purposes alone, irrespective of the value of \( n \)); and, (v) The best overall solutions produced by the MGA procedure will be very similar, if not identical, to the best overall solutions that would be produced by SO for function optimization alone.

5. Conclusions

Public environmental policy formulation is a very complicated process that can be impacted by many uncertain factors, unquantified issues and unmodelled objectives. This multitude of uncertain and competing dimensions force public policy-makers to integrate many conflicting sources of uncertainty into their decision process prior to final policy adoption. With the presence of so much uncertainty, it becomes unlikely that any single solution could ever be constructed that simultaneously satisfies all of the incongruent system requirements without a significant counterbalancing of the numerous tradeoffs involved. Any ancillary modelling techniques used to support the policy formulation process must simultaneously account for all of these features while being flexible enough to encapsulate the impacts from the inherent planning uncertainty. In this paper, a computational procedure was presented that showed how SO could be used to efficiently generate multiple, maximally different, near-best policy alternatives for difficult, stochastic, environmental problems and the effectiveness of this MGA approach was illustrated using a case study of municipal solid waste management planning. Since SO techniques can be adapted to model a wide variety of problem types in which system components are stochastic, the practicality of this approach can clearly be extended into many different types of operational and strategic planning applications containing significant sources of uncertainty.

References


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