Journal of Environmental Informatics 19(2) 58-69 (2012)

Journal of Environmental Informatics

www.iseis.org/jei

Modelling to Generate Alternative Policies in Highly Uncertain Environments: An Application to Municipal Solid Waste Management Planning

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Received 16 September 2010; revised 5 July 2011; accepted 6 August 2011; published online 22 June 2012

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 supporting decision models are constructed. Environmental policy formulation can prove additionally complicated because the various system components often contain considerable degrees of stochastic uncertainty. Furthermore, there are frequently numerous stakeholders with incompatible perspectives. Consequently, there are invariably unmodelled performance design issues, not apparent at the time of the construction of a decision support model, which can greatly impact the acceptability of its solutions. While a mathematically optimal solution may be the best solution to the modelled problem, it is frequently not the best solution to the real, underlying problem. Therefore, in public environmental policy formulation, it is generally preferable to create several quantifiably good alternatives that provide very different approaches to the problem. By generating a diverse set of solutions, it is hoped that some of these dissimilar alternatives can provide very different perspectives that may serve to satisfy the unmodelled objectives. This study shows how simulation-optimization (SO) modelling can be used to efficiently generate multiple policy alternatives that satisfy required system performance criteria in stochastically uncertain environments and yet are maximally different in the decision space. This new approach is very computationally efficient, since, in addition to finding the best solution to the problem, it permits the simultaneous generation of multiple, good solution alternatives in a single computational run of the SO algorithm rather than the multiple implementations required in other modelling-to-generate-alternatives procedures. The efficacy of this approach is specifically demonstrated using a previously studied waste management case from the Municipality of Hamilton-Wentworth, Ontario.

Keywords: modelling to generate alternatives, simulation-optimization, environmental decision making under uncertainty, planning and strategy

1. Introduction

In public sector decision making, numerous system objectives and requirements always exist that can never be explicitly included or apparent during the decision formulation stage. This is a common occurrence in situations where the final decisions must be constructed based not only upon clearly articulated and modelled objectives, but also upon environmental, political and socio-economic goals that are fundamentally subjective (Baugh et al., 1997; Brill et al., 1982; Liebman, 1976; Zechman and Ranjithan, 2004). Moreover, it may never be possible to explicitly express many of the subjective considerations in public policy formulation because there are generally numerous competing, adversarial stakeholder groups holding perspectives that are incompatible. Therefore many of these subjective aspects remain unknown, unquantified and unmodelled in the construction of any corresponding decision models. Thus, public sector decision-making typically involves complex problems that are riddled with competing performance objectives and possess design requirements which are very difficult to capture at the time that any supporting decision models are actually constructed (Brugnach et al., 2007; De Kok and Wind, 2003; Hipel and Ben-Haim, 1999; Mowrer, 2000; Walker et al., 2003). Environmental policy formulation can prove even more complicated because the various system components often also contain considerable stochastic uncertainty (Yeomans, 2008). Consequently, public sector environmental policy formulation often proves to be an extremely complicated and challenging undertaking (Janssen *et al.*, 2010; Loughlin et al., 2001).

Numerous ancillary modelling approaches have been proposed to support the policy formulation endeavour (Linton et al., 2002; Rubenstein-Montano et al., 2000) and for environmental policy determination, various deterministic mathematical programming techniques have been introduced (for example: Ferrell and Hizlan, 1997; Hasit and Warner, 1981; Haynes,

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ISSN: 1726-2135 print/1684-8799 online
 doi:10.3808/jei.201200209

1981; Lund, 1990; Lund et al., 1994; Marks and Liebman, 1971; Walker, 1976; Wenger and Cruz, 1990). However, while mathematically optimal solutions may provide the best results for the modelled problems, they are frequently not the best solutions for the underlying real problems due to the unmodelled issues and unquantified objectives not apparent at the time of model construction (Chang et al., 1982a, b; Gidley and Bari, 1986; Janssen et al., 2010; Loughlin et al., 2001). Furthermore, although optimization-based techniques are designed to create single best solutions, the presence of the unmodelled issues coupled with the system uncertainties and opposition from powerful stakeholders can actually lead to the outright elimination of any single (even an optimal) solution from further consideration (De Kok and Wind, 2003; Matthies et al., 2007; Yeomans, 2008; Zechman and Ranjithan, 2004).

In the environmental decision-making realm, there are frequently numerous stakeholder groups holding completely incongruent standpoints, essentially dictating that policy-makers must establish a decision framework that can concurrently consider numerous irreconcilable points of view (De Kok and Wind, 2003; Matthies et al., 2007; Yeomans, 2002, 2008). Consequently, from an environmental policy formulation standpoint it is generally preferable to be able to generate several alternatives that provide multiple, disparate perspectives to the problem under consideration (Huang et al., 1996; Janssen et al., 2010). Preferably these alternatives should all possess quantifiably 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. By generating this set of very different solutions, it is hoped that at least some of the dissimilar alternatives can be used to address the requirements of the unknown or unmodelled criteria to varying degrees of stakeholder acceptability.

In practice, most policy formulation proceeds with the policy-designers proposing a number of technologically feasible policy alternatives, which are then evaluated by estimating their performance and effect on the system. This stage is followed by a comparison of these alternatives in which the policy-designers select the specific option that best achieves their established system requirements. A significant disadvantage to this approach is that the policy-makers can only ever realistically construct a myopic subset of design alternatives, while the number of feasible options could prove to be extremely numerous. This limitation of policy generation in considering only a very narrow subset of possibilities, leads to the significant likelihood of entirely overlooking many better system design alternatives (Yeomans, 2008).

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., 1982; Chang et al., 1982a, b; Gidley and Bari, 1986; Loughlin et al., 2001; Rubenstein-Montano and Zandi, 1999; Rubenstein-Montano et al., 2000; Zechman and Ranjithan, 2004). The MGA approach was established to implement a much more systematic exploration of a solution space in order to generate a set of alternatives that are good within the modelled objective space while being maximally different in the decision space. Thus, a good MGA process should enable a thorough exploration of the decision space for good solutions while simultaneously allowing for unmodelled objectives to be considered when making the final decisions.

Notwithstanding their fundamental limitations, most mathematical programming approaches emanating from the planning research literature have focused almost exclusively upon producing optimal solutions to single-objective problem instances or, equivalently, generating noninferior solution sets to multi-objective problem formulations. While such algorithms may efficiently generate solutions to the derived complex mathematical models, whether their results actually establish "best" approaches for providing appropriate decisions to the underlying real problems is certainly questionable. Baugh et al. (1997), Brill *et al.* (1982) and Zechman and Ranjithan (2004) all supply numerous real world examples of this type of incongruent modelling duality. In particular, any search for good alternatives to problems known (or suspected) to contain unmodelled objectives must focus not only on the non-inferior solution set, but also necessarily on an exploration of the problem's inferior region. To illustrate the implications of an unmodelled objective on a decision search, assume that the optimal solution for a quantified, single-objective, maximization decision problem is $\boldsymbol{X}^*$ with corresponding objective value $Z1^*$. Now suppose that there exists a second, unmodelled, maximization objective $Z2$ that perhaps subjectively reflects environmental/-political acceptability. Let the solution $\boldsymbol{X}^a$, 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 $\boldsymbol{X}^a$ might be viewed as the best compromise solution to the real problem, it would clearly appear inferior to the solution $\boldsymbol{X}^*$ in the quantified model, since it must be the case that $Z1^a \leq Z1^*$. This observation implies that when unmodelled objectives are factored into the decision making process, mathematically inferior solutions for the modelled problem can potentially be optimal for the real problem. Therefore, when unmodelled objectives and unquantified issues might exist, different approaches are required in order to not only search the decision space for the noninferior set of solutions, but also to simultaneously explore the decision space for inferior alternative solutions to the modelled problem.

The primary motivation behind MGA is to produce a manageably small set of alternatives that are quantifiably 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 known modelled objective(s) yet very differently with respect to any unmodelled issues. By generating these good-but-different solutions, the policy-makers can explore alternatives that may satisfy the unmodelled objectives to varying degrees of stakeholder acceptability. Obviously the policy-setters must then conduct a subsequent comprehensive comparison of the alternatives to determine which options would most closely satisfy their very specific circumstances. Thus, an MGA approach should necessarily be considered as one of decision support rather than of explicit solution determination.

As mentioned earlier, the components of many environmental systems frequently contain considerable stochastic uncertainty. Hence, deterministic MGA methods are rendered relatively unsuitable for most environmental policy implementation situations, since they provide no effective mechanism with which to integrate these system uncertainties directly into the construction of their solutions (Brown et al., 1974; Coyle, 1973; Liebman, 1976; Gottinger, 1986; MacDonald 1996; Tchobanoglous et al., 1993). Various Monte Carlo simulation approaches have been incorporated into environmental planning to circumvent some of these uncertainty shortcomings (Bodner et al., 1970; Baetz, 1990; Wang et al., 1994; Openshaw and Whitehead, 1985). However, while simulation provides an effective means for comparing stochastic system behaviours, it provides no formal mechanism for actually calculating good system solutions.

Yeomans et al., (2003) incorporated stochastic uncertainty directly into environmental planning using an approach referred to as simulation-optimization (SO). SO is a family of optimization techniques that incorporates inherent stochastic uncertainties expressed as probability distributions directly into its computational procedure (Fu, 2002; Kelly, 2002). The approach of Yeomans et al. (2003) focused solely upon the "function optimization" aspects of the modelled systems, with the goal being to determine single best system policies. While SO holds considerable potential for application to a wide range of stochastic problems, it cannot be considered universally applicable due to its accompanying solution time issues (Fu, 2002; Kelly, 2002; Lacksonen, 2001). Huang et al. (2005) and Yeomans (2005, 2007, 2010) have examined several approaches to accelerate the search times and solution quality of SO in its function optimization capacity.

To address the deficiencies of the deterministic MGA methods, Yeomans (2002) demonstrated that SO could be used to generate multiple policy options which simultaneously integrated stochastic uncertainties directly into each generated alternative. Since computational aspects can negatively impact SO's optimization capabilities, these difficulties clearly also extend into its use as an MGA procedure (Yeomans, 2008). 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 could ensure that the created alternatives were sufficiently different in decision variable structure from one another to be considered an effective procedure.

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 and Ranjithan (2004) that has been specifically modified to address the heavy computational burdens inherent in SO. This new stochastic MGA approach is very computationally efficient, since it permits the concurrent generation of multiple, quantifiably good solution alternatives, guaranteed to be as different as possible from one another, in a single computational run of the SO algorithm in contrast to the repeated multiple implementations required in most other MGA procedures. This study illustrates the efficacy of this new SO procedure's MGA capabilities by testing it on the municipal solid waste (MSW) management study taken from Yeomans et al. (2003).

2. An Efficient Simulation-Optimization Approach for Modelling to Generate Alternatives

In this section, the computationally efficient, co-evolutionary MGA procedure, capable of incorporating stochastic uncertainty directly into its generated alternatives, is developed using a modified SO adaptation of Zechman and Ranjithan (2004) (see Yeomans, 2009).

Determining optimal solutions to large stochastic problems proves to be very complicated when system uncertainties have to be incorporated directly into the solution procedures (Fu, 2002). If the objective function for an optimization problem is represented by F, the problem's feasible region is given by D, and the problem contains n decision variables expressed in vector form as $\boldsymbol{X} = [X_1, X_2, \ldots, X_n]$, then the corresponding mathematical programming problem is to optimize $F(\boldsymbol{X})$ subject to $\boldsymbol{X} \in D$. When stochastic conditions exist, values for the parameters, constraints and objective(s) can only ever be efficiently estimated via simulation. While simulation presents the means for comparing results, it does not provide a mechanism for constructing optimal solutions to these problems.

SO is a broadly defined family of solution approaches that combines simulation with some underlying optimization method for stochastic optimization. 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, $\boldsymbol{X}$, is evaluated via simulation. As simulation is computationally intensive, an optimization component is employed to guide the search for solutions through the problem's feasible region using as few simulation runs as necessary (Azadivar, 1999; Fu, 1994, 2002; Law and Kelton, 2000). Lacksonen (2001) contrasted the performance of the various SO search strategies and found that evolutionary procedures clearly proved to be the most robust. In this paper, the SO solution search procedure is directed by an evolutionary algorithm.

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. Because of the system's stochastic components, all performance measures are necessarily statistics calculated from the responses generated in the simulation module. The fitness or quality 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 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 become the inputs to the evolutionary module where the next solution population is created via the evolutionary algorithm. The evolutionary module evaluates the entire population in each generation of the solution search and evolves the search from its current population to a subsequent one. 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. The evolutionary module continuously evolves the system toward improved solutions in subsequent populations and ensures that the solution search does not become fixated at some local optima. This alternating, two-phase search process terminates when an appropriately stable system state has been attained (Azadivar and Tompkins, 1999; Pierreval and Tautou, 1997; Yeomans, 2008). The optimal solution produced by the procedure is the single best solution found over the course of the entire search.

One shortcoming of essentially all of the preceding MGA techniques has been that they have generally been based upon deterministic mathematical programming methods and consequently have no mechanism to effectively incorporate uncertainty into their solution construction. Fortunately, the evolving population-based search strategy of evolutionary SO provides a computational mechanism for integrating the inherent stochastic uncertainties directly into each of the generated solutions while simultaneously generating options that may never have been proposed or considered by decision-makers. By design, evolutionary search algorithms maintain populations of solutions throughout their searching phases. When evolving from one population to a subsequent one, the relatively weaker candidate solutions within the population become progressively replaced by better solutions in the evolutionary survival-of-the-fittest analogy. Therefore, upon termination, SO procedures have not only produced single best answers from their solution searches, but have also concurrently created a set of several quantifiably good solutions residing in their highly fit, terminal populations. This concept is used in the new co-evolutionary SO MGA approach.

In order to properly motivate the procedure, it is necessary to provide a more formal definition of the underlying, fundamental goals of an MGA process (Brill et al., 1982; Zechman and Ranjithan, 2004). Suppose the optimal solution to an original mathematical model is $\boldsymbol{X^*}$ with objective value $Z^* = F(\boldsymbol{X^*})$. The following model can then be solved to generate an alternative solution that is maximally different from $\boldsymbol{X}^*$:

$$Max \quad \Delta = \sum_i |X_i - X_i^*| \qquad [P1]$$

$$\text{s.t. } \boldsymbol{X} \in D$$

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

where Δ 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. For example, if the original objective is to minimize cost and the least cost is \$100, then the target could be set at \$110 thereby allowing for solutions that exceed the original model's optimal solution by no more than 10%. To generate additional alternatives, the target T is progressively incremented such that the new solution found is maximally different from the previously generated alternatives. This alternative generation process terminates when either no new alternative solution can be found or the prescribed number of alternatives has been generated.

A direct approach to generate alternatives with the SO algorithm would be to iteratively solve the maximum difference model, P1, using SO by incrementally updating the target T whenever a new alternative must be produced. This approach would be somewhat similar in scope to the original Hop, Skip, and Jump (HSJ) method of Brill et al. (1982) in which an initial problem formulation is optimized and then supplementary alternatives are generated by systematically adjusting the target constraint to force the creation of suboptimal solutions. While this approach is straightforward, it would require repeated execution of the SO algorithm, which would be extremely computationally intensive (Yeomans, 2008).

The new MGA procedure is designed to generate a small number of good but maximally different alternatives, as defined by P1, in a single run of the SO procedure (i.e. the same number of runs as if SO were used solely for function optimization) and is based upon the concept of co-evolution. In this new approach, pre-specified stratified subpopulation ranges within the evolutionary algorithm's overall population are established that collectively evolve the search toward the formation of the stipulated number of very different solution alternatives. Each desired solution alternative is represented by each respective 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 both the modelled objective(s) and by how far away they are from all of the other solutions in the decision space as represented in P1. Thus, the evolution of solutions in each subpopulation is directly influenced by those solutions contained in the other subpopulations, forcing the evolution of each subpopulation towards good but maximally distant regions of the decision space. This co-evolutionary concept enables the simultaneous search for, and production of, a set of quantifiably good solutions that are maximally different from each other (Yeomans, 2009).

By using the co-evolutionary concept, it becomes possible to implement an SO-based MGA procedure that produces alternatives which possess objective function bounds that are somewhat analogous, but superior, to those created by an HSJ-type approach. While each alternative produced by an HSJ procedure is maximally different only from the single, overall optimal solution together with an objective value which is at least x% different from the best objective (i.e. x = 1%, 2%, etc.), the new co-evolutionary procedure is able to generate alternatives that are no more than x% different from the overall optimal solution but with each one of these solutions being as maximally different as possible from every other generated alternative that is produced in terms of the solution structure of their decision variables according to P1. Co-evolution is also a much more efficient process than HSJ in that it exploits the population-based searches of evolutionary algorithms in order to generate the multiple maximally different solution alternatives simultaneously. Namely, while an HSJ-styled approach would be required to run n different times in order to generate n different alternatives, the new algorithm need be run only a single time to produce its entire set of alternatives irrespective of the value of n. Hence, it is a much more computationally efficient procedure.

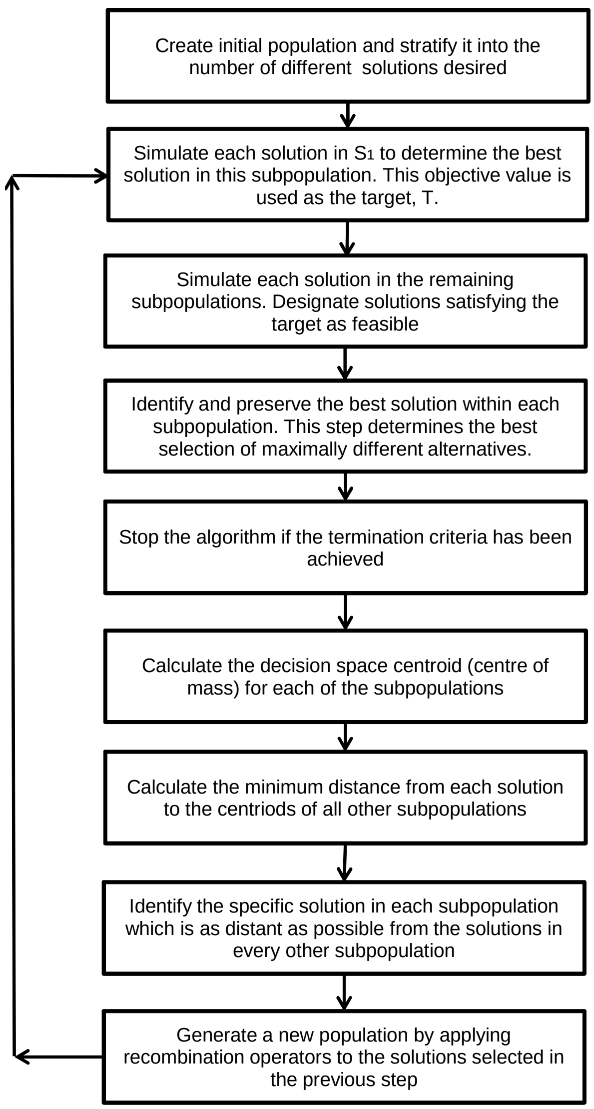

Figure 1. Flowchart of the Co-Evolutionary MGA Procedure.

The steps in the co-evolutionary algorithm are as follows:

1. Create an initial population stratified into P equally-sized subpopulations. The value for P typically must be established *a priori* by decision-maker. P represents the desired number of alternative solutions to be generated. S_p represents the p^{th} subpopulation set of solutions, $p = 1, 2, \ldots, P$ and there are K solutions contained within each S_p. S_1 is the subpopulation dedicated to the search for the overall optimal solution to the modelled problem. The best solution residing in S_1 is employed to establish the benchmarks for the relaxation constraints used to create the maximally different solutions as in P1.

2. Evaluate each of the solutions in S_1 using simulation and identify the best solution with respect to the modelled objective.

3. In $S_p, p = 2, 3, \ldots, P$, use the simulation module to evaluate each of the solutions with respect to the modelled objecttive. Solutions meeting the target constraint are designated as feasible, while all other solutions are designated as infeasible.

4. Apply an appropriate elitism operator to each S_p to preserve the best individual in each subpopulation. In S_1, this is the best solution evaluated with respect to the modelled objective. In all other subpopulations S_p, $p = 2, 3, \ldots, P$, the best solution is the feasible solution most distant in decision space from all of the other subpopulations (the distance measure is defined in Step 7). If all solutions in S_p are infeasible, then this is the best individual solution with respect to the modelled objective. This step simultaneously selects a set of alternatives that respectively satisfy different values of the target T while being as far apart as possible (i.e. maximally different in the sense of P1) from the solutions generated in each of the other subpopulations. Note that by the co-evolutionary nature of this algorithm, the alternatives are simultaneously generated in one pass of the procedure rather than the P implementations suggested by the necessary increments to T in problem P1.

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}, $i = 1, 2, \ldots, N$, in solution $k = 1, 2, \ldots, K$, of S_p, $C_{ip} = (1/K) * \sum_k X_{ikp}$. Each centroid represents the N-dimensional centre of mass for the solutions in each of the respective subpopulations, p. In the calculation shown, each dimension of each centroid is computed as the average value of that decision variable over all of the values for that variable within the respective subpopulation. Alternatively, the centroid could be calculated as a fitness-weighted average or by some other appropriately defined measure.

7. For each solution $k = 1, 2, \ldots, K$, in each S_q, $q \neq 1$, calculate D_{kq} , a distance measure between that solution and all other subpopulations. $D_{kq} = \text{Min } \{|X_{ikp} - C_{ip}|; p = 2, \ldots, P; p \neq q\}$. 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_1, the selection is with respect to the modelled objective. In each S_p, $p \neq 1$, the selection is based on the fitness of the solution with respect to the modelled objective(s) as well as its

distance from all 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, or 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. The goal of maximal difference is to force solutions from one subpopulation to be as far apart as possible in the decision space from the solutions of each of the other subpopulations as required in P1. This step identifies the specific solution in each subpopulation which is as distant as possible from the solutions in all of the other subpopulations.

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

A schematic flowchart illustrating the steps involved in the co-evolutionary procedure appears in Figure 1.

By adopting this co-evolutionary MGA methodology, multiple maximally different design options would be created that meet established system criteria, while simultaneously remaining acceptable and implementable in practice. The evolutionary SO procedure used within this MGA context will have generated a set of very good policy alternatives and, by the nature of evolutionary searches, most of these options would never have been considered by planners during their normal, more myopic policy-setting phase. SO's ability to directly integrate the stochastic uncertainty into the option generation produces major practical benefits in comparison to deterministic approaches and, since environmental policy formulation problems contain so many uncertain components, reality dictates that such an approach would be requisite in order to produce one or more realistically acceptable solution alternatives.

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

The efficacy of this new co-evolutionary SO MGA procedure will be illustrated using the municipal solid waste management planning study of Hamilton-Wentworth, Ontario taken from Yeomans et al. (2003). The MSW management system within the region is a very complicated process which is impacted by economic, technical, social, environmental, legislational and political factors. Prior to the study of Yeomans et al. (2003), the municipality had not been able to effectively incorporate inherent uncertainties into their planning processes and, therefore, had not performed effective systematic planning for the flow of wastes within the region. While this section briefly outlines the case, more extensive details and descriptions can be found in both Yeomans et al. (2003) and Yeomans (2008).

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; Hamilton, Dundas, Ancaster, Flamborough, Stoney Creek, and Glanbrook. The Municipality is considered the industrial centre of Canada, although it simultaneously incorporates diverse areas of not only heavy industrial production, but also densely populated urban space, regions of significant suburban development, and large tracts of rural/agricultural land. The MSW system within Hamilton-Wentworth needed to satisfy the waste disposal requirements of its half-million residents who, collectively, produced 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 at Glanbrook; three waste transfer stations located in Dundas (DTS), in East Hamilton at Kenora (KTS), and on Hamilton Mountain (MTS); a household recycling program contracted to and operated by the Third Sector Employment Enterprises; 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 Glanbrook for landfilling. 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, produces 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 generates 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 produce 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 policy 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 overriding system uncertainties.

The complete mathematical model for MSW planning in Hamilton-Wentworth can be found in the appendix, while more extensive details and descriptions of it appear in Yeomans et al. (2003). This mathematical formulation was used not only to examine the existing municipal MSW system, but also to prepare the municipality for several potentially enforced structural changes to its operating conditions. Yeomans et al. (2003) examined three likely future scenarios, with each scenario involving potential incinerator operations. Scenario 1 considered the existing MSW management system and corresponded to a *status quo* case. Scenario 2 examined what would occur should the incinerator operate at its upper design capacity; corresponding to a situation in which the municipality would landfill as little waste as possible. Scenario 3 permitted the incinerator to operate anywhere within its design capacity range; from being closed completely to operating up to its maximum capacity. Yeomans et al. (2003) ran SO for a 24-hour period to determine best solutions for each scenario. For the existing system (Scenario 1), a solution that would never cost more than $20.6 million was constructed. For Scenarios 2 and 3, Yeomans et al. (2003) produced optimal solutions costing no more $22.1 million and $18.7 million, respectively. In all of these scenarios, SO was used exclusively as a function optimizer with the goal being to produce only single best solutions.

As outlined earlier, when public policy planners are faced with difficult and 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 for the three MSW system scenarios, it would be possible to place extra target constraints into the original SO model which would force the generation of solutions that were structurally different from their respective, initial optimal solutions. Suppose for example that ten additional planning alternative options were created according to P1 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 10 times for each scenario (i.e. 30 additional runs of the SO procedure), it would be possible to create the prescribed number of alternative policies for MSW planning.

However, to improve upon the process of running thirty separate additional instances of the computationally intensive SO algorithm to generate these solutions, the co-evolutionary MGA procedure described in the previous section need be run exactly once for each scenario. The evolutionary parameters used for this computational experiment were a population size of 220 (i.e. a subpopulation size of 20 for the optimal solution's subpopulation and for each of the 10 required alternatives), a maximum number of iterations of 300 (together with an additional check for solution convergence), a crossover parameter of 40% and a mutation rate of 5%. The co-evolutionary MGA procedure was coded in Visual Basic and implemented on a Dell Precision M4300 laptop running at 2.4 GHz. This experimentation produced the 30 additional alternatives shown in Table 1. Each column of the table shows the overall system costs for the 10 maximally different options generated for each of the three scenarios. 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 generated by the co-evolutionary MGA algorithm are as 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 for Scenarios 1, 2 and 3

Annual MSW System Costs	Scenario 1	Scenario 2	Scenario 3
Overall "Optimal" Solution	20.6	22.1	18.7
Best 1% Solution	20.7	22.2	18.8
Best 2% Solution	20.9	22.4	18.9
Best 3% Solution	21.1	22.6	19.1
Best 4% Solution	21.4	22.7	19.4
Best 5% Solution	21.4	23.1	19.5
Best 6% Solution	21.8	23.3	19.7
Best 7% Solution	22.0	23.6	19.9
Best 8% Solution	22.2	23.8	20.0
Best 9% Solution	22.3	23.9	20.1
Best 10% Solution	22.5	24.1	20.3

Furthermore, it should also be explicitly noted that the alternatives created 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 each and every one of the other alternatives generated, while simultaneously guaranteeing that their objective values deviate from the overall best objective by *no more* than the specified targets of 1, 2, …, 10%, respectively. Thus, the alternatives generated in this MGA approach are very different from those produced in the more straightforward incremental HSJ-style of target setting, while simultaneously establishing much more robust guarantees of solution quality.

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 the originally modelled problem, itself. Table 2 clearly highlights how the alternatives generated in S_1 by the new MGA procedure are all "good" with respect to their best overall cost measurements relative to the optimal solutions found in Yeomans et al. (2003). It should be explicitly noted that the cost of the overall best solutions produced by the MGA procedure (i.e. the best solutions found in S_1) are actually identical to the ones found in the function optimization of Yeomans et al. (2003) for each scenario. This is obviously not a coincidence because any expansion of the population size in the SO procedure to include the additional subpopulations S_2, S_3,…, S_{11} does not detract from its evolutionary capabilities to find the best, function optimization solution in subpopulation S_1. Hence, in addition to its alternative generating capabilities, the MGA procedure simultaneously also performs exceedingly well with respect to its role as a function optimizer.

This example has demonstrated how co-evolutionary SO

MGA modelling can be used to efficiently generate multiple, quantifiably good policy alternatives that satisfy required system performance criteria according to prespecified bounds within stochastically uncertain environments and yet remain maximally different from each other 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 stochastic 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 all of their structures are as mutually and maximally different from each other as possible (i.e. these differences are not just simply different from the overall optimal solution as in the HSJ-style approach to MGA); (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, SO MGA needs to run exactly the same number of times that SO would need to be run for function optimization purposes alone – namely once – 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.

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

4. 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 forces 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, therefore, somehow simultaneously account for all of these features while being flexible enough to encapsulate the impacts from the inherent planning uncertainty.

Table 2. Best Annual MSW Performance Costs (in millions of $) Found for Scenarios 1, 2 and 3

	Scenario 1	Scenario 2	Scenario 3
Yeomans et al. (2003) using SO	20.6	22.1	18.7
Best Solution Found Using Co-Evolutionary Algorithm	20.6	22.1	18.7

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. MSW systems provide an ideal testing ground for illustrating a wide variety of modelling techniques used to support environmental public policy formulation, since they possess all of the prevalent incongruencies and system uncertainties that so often exist in complex planning processes.

In its stochastic MGA capacity, SO was shown to be able to efficiently produce numerous solutions possessing the requisite characteristics of the system, with each generated alternative providing a very different planning perspective. However, unlike deterministic MGA methods, SO can incorporate stochastic uncertainties directly into the generation of these alternatives. Because an evolutionary method guides the search, SO actually provides a formalized, population-based mechanism for considering many more solution options than would be created by other MGA approaches. 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.

Acknowledgement. This research was supported in part by grant OGP0155871 from the Natural Sciences and Engineering Research Council. The authors would like to thank the editor and five anonymous referees for providing numerous helpful comments and suggestions which lead to a substantially improved paper.

Appendix: Mathematical Model for MSW Planning in Hamilton-Wentworth

In the model, the various districts from which waste originates are identified using subscript i; where $i = 1, 2, \ldots, 17$, denotes the originating district. The transfer stations are denoted by subscript j, in which $j = 1, 2, 3$, represents the number assigned to each transfer station, where DTS = 1, KTS = 2 and MTS = 3. Subscript k, $k = 1, 2, 3$, identifies the specific waste management facility, with Landfill = 1, SWARU = 2, and Third

Sector = 3. The decision variables for the problem are designated by x_{ij}, y_{ik} and z_{ik} where x_{ij} represents the proportion of solid waste sent from district i to transfer station j; y_{ik} corresponds to the proportion of waste sent from transfer station j to waste management facility k, and z_{ik} corresponds to the proportion of waste sent from district i to waste management facility k. For notational brevity, and also to reflect the fact that no district is permitted to deliver their waste directly to the landfill, define $z_{i1} = 0$, for $i = 1, 2, \ldots, 17$.

In the model, any stochastically uncertain parameter A is represented by the notation A. The cost for transporting one ton of waste from district i to transfer station j is denoted by $\overleftrightarrow{tx}_{ij}$, that from transfer station j to waste management facility k is represented by $\overleftrightarrow{ty}_{jk}$, and that from district i to waste management facility k is $\overleftrightarrow{tz}_{ik}$. The per ton cost for processing waste at transfer station j is $\overleftrightarrow{\delta}_j$ and that at waste management facility k is $\overleftrightarrow{\rho}_k$. Two of the waste management facilities can produce revenues from processing wastes. The revenue generated per ton of waste is $\overleftrightarrow{r}_2$ at SWARU and $\overleftrightarrow{r}_3$ at the Third Sector recycling facility. The minimum and maximum processing capacities at transfer station j are $\overleftrightarrow{K}_j$ and $\overleftrightarrow{M}_j$, respectively. Similarly, the minimum and maximum capacities at waste management facility k are $\overleftrightarrow{L}_k$ and $\overleftrightarrow{N}_k$, respectively. The quantity of waste, in tons, generated by district i is $\overleftrightarrow{W}_i$, and the proportion of this waste that is recyclable is $\overleftrightarrow{a}_i$. The proportion of recyclable waste flowing into transfer station j is $\overleftrightarrow{RW}_j$. The proportion of residue (residual wastes such as the incinerated ash at SWARU) generated by waste management facility j is $\overleftrightarrow{Q}_j$, where $\overleftrightarrow{Q}_1 = 0$ by definition. This waste residue must be shipped to the landfill for final disposal.

Formulating any specific MSW policy formulated for Hamilton-Wentworth would require the determination of a decision variable solution satisfying constraints (2) to (31) and would be evaluated by its resulting cost found using objective (1).

Cost/Revenue Objective:

$$\text{Minimize Cost} = \sum_{p=1}^{5} T_p + \sum_{q=1}^{6} P_q + \sum_{r=2}^{3} R_r \tag{1}$$

Subject to:

Transportation Cost Constraints:

$$T_1 = \sum_{i=1}^{17}\sum_{j=1}^{3} \overleftrightarrow{tx}_{ij} x_{ij} \overleftrightarrow{W}_i \tag{2}$$

$$T_2 = \sum_{i=1}^{17}\sum_{k=1}^{3} \overleftrightarrow{tz}_{ik} z_{ik} \overleftrightarrow{W}_i \tag{3}$$

$$T_3 = \sum_{i=1}^{17}\sum_{j=1}^{3}\sum_{k=1}^{3} \overleftrightarrow{ty}_{jk} y_{jk} x_{ij} \overleftrightarrow{W}_i \tag{4}$$

$$T_4 = (\overleftrightarrow{t}sl)\overleftrightarrow{Q}_2 \sum_{i=1}^{17} \overleftrightarrow{W}_i [z_{i2} + \sum_{j=1}^{3} y_{j2} x_{ij}] \tag{5}$$

$$T_5 = (\overleftrightarrow{t}tl)\overleftrightarrow{Q}_3 \sum_{i=1}^{17} \overleftrightarrow{W}_i [z_{i3} + \sum_{j=1}^{3} y_{j3} x_{ij}] \tag{6}$$

Waste Processing Cost Constraints:

$$P_1 = \overleftrightarrow{\rho}_1 \sum_{i=1}^{17} \overleftrightarrow{W}_i \sum_{k=1}^{3} [\overleftrightarrow{Q}_k z_{ik} + \sum_{j=1}^{3} x_{ij} y_{jk}] \tag{7}$$

$$P_2 = \overleftrightarrow{\rho}_2 \sum_{i=1}^{17} \overleftrightarrow{W}_i [z_{i2} + \sum_{j=1}^{3} x_{ij} y_{j2}] \tag{8}$$

$$P_3 = \overleftrightarrow{\rho}_3 \sum_{i=1}^{17} \overleftrightarrow{W}_i [z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3}] \tag{9}$$

$$P_4 = \overleftrightarrow{\delta}_1 \sum_{i=1}^{17} x_{i1} \overleftrightarrow{W}_i \tag{10}$$

$$P_5 = \overleftrightarrow{\delta}_2 \sum_{i=1}^{17} \overleftrightarrow{W}_i [x_{i2} + \overleftrightarrow{Q}_3 (z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3})] \tag{11}$$

$$P_6 = \overleftrightarrow{\delta}_3 \sum_{i=1}^{17} x_{i3} \overleftrightarrow{W}_i \tag{12}$$

Revenue Constraints:

$$R_2 = \overleftrightarrow{r}_2 \sum_{i=1}^{17} \overleftrightarrow{W}_i [z_{i2} + \sum_{j=1}^{3} x_{ij} y_{j2}] \tag{13}$$

$$R_3 = \overleftrightarrow{r}_3 \sum_{i=1}^{17} \overleftrightarrow{W}_i [z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3}] \tag{14}$$

Transfer Station Capacity Limits Constraints:

$$\sum_{i=1}^{17} x_{i1} \overleftrightarrow{W}_i \le \overleftrightarrow{M}_1 \tag{15}$$

$$\sum_{i=1}^{17} \overleftrightarrow{W}_i [x_{i2} + \overleftrightarrow{Q}_3 (z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3})] \le \overleftrightarrow{M}_2 \tag{16}$$

$$\sum_{i=1}^{17} x_{i3} \overleftrightarrow{W}_i \le \overleftrightarrow{M}_3 \tag{17}$$

$$\sum_{i=1}^{17} x_{i1} \overleftrightarrow{W}_i \ge \overleftrightarrow{K}_1 \tag{18}$$

$$\sum_{i=1}^{17} \overleftrightarrow{W}_i [x_{i2} + \overleftrightarrow{Q}_3 (z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3})] \ge \overleftrightarrow{K}_2 \tag{19}$$

$$\sum_{i=1}^{17} x_{i1} \overleftrightarrow{W}_i \ge \overleftrightarrow{K}_3 \tag{20}$$

Landfill, SWARU and Third Sector Recycling Facility Capacity Limits Constraints:

$$\sum_{i=1}^{17} \vec{W}_i \sum_{k=1}^{3} [\vec{Q}_k z_{ik} + \sum_{j=1}^{3} x_{ij} y_{jk}] \leq \vec{N}_1 \tag{21}$$

$$\sum_{i=1}^{17} \vec{W}_i [z_{i2} + \sum_{j=1}^{3} x_{ij} y_{j2}] \leq \vec{N}_2 \tag{22}$$

$$\sum_{i=1}^{17} \vec{W}_i [z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3}] \leq \vec{N}_3 \tag{23}$$

$$\sum_{i=1}^{17} \vec{W}_i [z_{i2} + \sum_{j=1}^{3} x_{ij} y_{j2}] \geq \vec{L}_2 \tag{24}$$

$$\sum_{i=1}^{17} \vec{W}_i [z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3}] \geq \vec{L}_3 \tag{25}$$

Mass Balance Constraints:

$$\sum_{j=1}^{3} x_{ij} + \sum_{k=1}^{3} z_{ik} = 1,\ i = 1, 2, \ldots, 17 \tag{26}$$

$$\sum_{j=1}^{3} x_{ij} \vec{R} W_j + z_{i3} \leq \vec{a}_i,\ i = 1, 2, \ldots, 17 \tag{27}$$

$$\sum_{k=1}^{3} y_{jk} = 1,\ j = 1, 2, 3 \tag{28}$$

$$\sum_{i=1}^{17} \vec{W}_i [x_{i2} + \vec{Q}_3 (z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3})] = \sum_{i=1}^{17} \sum_{k=1}^{3} x_{i2} \vec{W}_i y_{2k} \tag{29}$$

$$\sum_{i=1}^{17} x_{ij} \vec{W}_i y_{j3} = \vec{R} W_j \sum_{i=1}^{17} x_{ij} \vec{W}_i \tag{30}$$

$$x_{ij} \geq 0,\ y_{jk} \geq 0,\ z_{ik} \geq 0,\ i = 1, 2, \ldots, 17;\ j = 1, 2, 3;\ k = 1, 2, 3 \tag{31}$$

In the objective function (1), the total transportation costs for wastes generated are provided by equations (2) to (6). Equation (2) calculates the transportation costs for waste flows from the districts (i.e. the cities and towns) to the transfer stations, while equation (3) provides the costs for transporting the waste from the districts directly to the waste management facilities. The total cost for transporting waste from the transfer facilities to the waste management facilities is determined in equation (4). The transportation costs for residue disposal created at SWARU and the Third Sector are given by equations (5) and (6), respectively. The total processing costs for the transfer stations and waste management facilities are expressed in (7) through (12). Here, P_k represents the processing costs at waste management facility k, $k = 1, 2, 3$, and $P_{(j+3)}$ represents the processing costs at transfer station j, j = 1, 2, 3. The processing cost, P_1, in (7) indicates that the landfill receives wastes from both SWARU and the Third Sector in addition to the waste sent from the transfer stations. The relationship specifying the processing costs at KTS, P_5 in (11), is more complicated than for DTS and MTS, since KTS must also process the Third Sector's unrecyclable residue (this waste processing pattern can also be observed in equations (16) and (19)) and this residue may have been sent there directly from the districts or from the other transfer stations. The revenue generated by SWARU, R_2, and by the Third Sector, R_3, are determined by expressions (13) and (14). All of these cost and revenue elements are amalgamated into objective function (1).

Although several alternative objectives for (1) were analyzed in Yeomans et al. (2003), determining solutions which minimized the maximum cost satisfied the paramount risk aversion characteristics exhibited by the municipal government. Since municipal budgets generally establish fixed annual dollar amounts to fund their programs, municipalities tend to be extremely risk averse and aim to avoid any potential outcomes that might lead to an overspending of their budgeted allocations. Therefore, focusing upon the maximum objective introduced practical advantages from a budget-setting standpoint for municipalities that must fund programs solely through taxation. The nature of these types of solutions might produce relatively high costs on average, but would guarantee that municipal spending would never exceed the value of the maximum objective found. Hence, this is the objective employed for the fitness function in the co-evolutionary algorithm.

Upper and lower capacity limits placed upon the transfer stations DTS, KTS and MTS, are provided by constraints (15) through (20), while capacity limits established for the landfill, SWARU and the Third Sector are given by (21) to (25). The waste processing relationship for the landfill is more complicated than for the other waste management facilities, since the landfill receives residue from both SWARU and the Third Sector. Furthermore, while there is no lower operating requirement placed upon the use of the landfill, both SWARU and the Third Sector require minimum levels of activity in order for their ongoing operations to remain economically viable. Mass balance constraints must also be included to ensure that all generated waste is disposed and that the amount of waste flowing into a transfer facility matches the amount flowing out of it. Constraint (26) ensures the disposal of all waste produced by each district. Recyclable waste disposal is established by constraint (27). In (27), it is recognized that not all recyclable waste produced at a district is initially sent to the Third Sector recycling facility (i.e. some recyclable waste may initially be discarded as "regular" garbage) and that some, but not all, recyclable waste received at a transfer station is subsequently sent for recycling. The expression in (28) ensures that all waste received by each transfer station must be sent to a waste management facility. Equation (29) provides the mass balance constraint for the wastes entering and leaving KTS (which handles more complicated waste patterns than the other two transfer stations). Constraint (30) describes the mass balance requirement for recyclable wastes received by the transfer stations that are then forwarded to the Third Sector. Finally, (31) establishes non-negativity requirements for the decision variables.

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