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Combining Simulation with Evolutionary Algorithms for Optimal Planning Under Uncertainty: An Application to Municipal Solid Waste Management Planning in the Reginonal Municipality of Hamilton-Wentworth

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ABSTRACT. Many uncertain factors exist in the planning for Municipal Solid Waste (MSW) management. In this paper, for the first time an evolutionary algorithm is combined with simulation to determine solutions for the MSW management problem. This new procedure is applied to real case data taken from the Regional Municipality of Hamilton-Wentworth in the province of Ontario and the solutions are compared to the outputs from an earlier study. It can be shown that improved solutions to this problem can be obtained and that this approach provides many practical planning and implementation benefits for problems operating under uncertain conditions.

Keywords: Decision making under uncertainty, genetic algorithms, municipal solid waste management, simulation

1. Introduction

In a recent article, Huang et al. (1998) studied the policy problem of collection, allocation, and disposal planning for municipal solid waste (MSW) management within the Regional Municipality of Hamilton-Wentworth; a region located at the western-most tip of Lake Ontario. Solid waste (or trash) can be disposed of either by recycling, by incineration, or by burial in a landfill site. The collection, transportation, and disposal methods used for processing solid waste can consume a significant portion of the municipality's operating budget. Since the municipalities of Ontario must currently function in an era of "no new taxes", with their operating budgets financed solely through municipal taxation, it is imperative that the waste-flow allocation policy employed can be demonstrably proven to operate as effectively and efficiently as possible. Hence, in the 1990s, the solid waste managers for Hamilton-Wentworth sought some method to determine whether their existing allocation and disposal policy was the best one and, if not, could be used to produce or suggest a more efficient policy. Additionally, due to the imminent restructuring of municipal boundaries by the Government of Ontario (the amalgamation of several neighbouring municipalities into a single, new "mega city") and to annually updated environmental regulations, it was desirable to devise a technique that could be effectively employed for additional "what-if" type policy analysis and planning. A detailed summary of this resulting method, together with its results, is provided in Huang et al. (1998).

Municipal solid waste planning is not a new problem. In earlier research, Haynes (1981) and Wenger & Cruz (1990) described how various "traditional" optimization techniques had been applied to solve several different types of complicated waste-management problems. Examples of specific applications of optimization methods in solid waste management can be found in the work of Marks & Liebman (1971), the simplex with forcing trials technique (Walker, 1976), the Environmental Protection Agency's waste resource allocation program (Hasit & Warner, 1981), and the analysis of recycling/recovery operations (Lund, 1990; Lund et al., 1994). In general, optimization procedures are used to determine a single best solution to a problem. It has been demonstrated that the optimization procedures described by these types of models are applicable only to well-structured problems (Coyle, 1973, Brown et al. 1974; Liebman, 1975). Unfortunately, a variety of factors increase the complexity of solid-waste planning rendering many of the components ill-structured and uncertain (Gottinger, 1986; Tchobanoglous et al. 1993; MacDonald, 1996). Simulation studies have been developed to circumvent several of these uncertainty shortcomings in solid-waste planning (Bodner et al., 1970; Openshaw & Whitehead, 1985; Baetz, 1990; Wang et al., 1994; Lawver et al., 1990). Such Monte Carlo models tend to be used for detailed analysis of proposed solutions (such as a solution that may have been found by optimization, or suggested by some other means), and can also be used to evaluate the inherent uncertain relationships that exist within systems being modeled. Hence, simulation studies, in and of themselves, do not find a solution, but have been used to compare and evaluate several solutions; the best of these solutions then being selected for implementation.

Recently, Montano & Zandi (1999) used a genetic algorithm-based procedure for designing solid-waste policy plans.

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Usually genetic algorithms are implemented as (heuristic based) function optimizers to find a single best solution to a problem. However, due to the evolutionary characteristics inherent in genetic algorithms, these procedures actually produce a *set* of several solutions (its population) upon termination. Montano & Zandi (1999) exploited this set-feature of genetic algorithms to devise a family of good policy options. Further evaluation is then undertaken to determine which member of this solution set most appropriately satisfies the needs of the solid-waste system under study. Although this approach effectively combines the concepts of finding a good solution with the evaluation of several potential solutions, it does not provide a means to overcome the uncertain components inherent within solid-waste systems.

Since many of the solid-waste system components in the Hamilton-Wentworth case were uncertain, the quality of the available information in the municipality was not considered to be sufficiently accurate enough to be stated strictly as deterministic numbers; a condition requisite for the implementation of the aforementioned optimization approaches. Consequently, traditional optimization methods were not applicable to this problem. However, the municipality's planners and engineers were quite comfortable in specifying the uncertain data as estimated interval ranges (i.e. as high and low estimates). Given this information, perhaps the most logical approach to judging the system's capabilities would be to find the objective or evaluative function values for their system operating under its best and worst case conditions given this interval data. Unfortunately, best case-worst case analysis often produces decision variable solutions for the two extremes which do not contain a set of stable intervals for generating decision alternatives (see Huang et al., 1998; Wallace, 2000) and could require an exponential period of time to correct (Budnick et al., 1988). A second logical and commonly prescribed approach to decision making under uncertainty (see Ravindran et al., 1987;Gal & Greenberg, 1997) would be to employ post-optimality analysis combining sensitivity analysis with parametric optimization. Such an approach is appropriate only when a problem has relatively few uncertain parameters and, unfortunately, the Hamilton-Wentworth problem contained a large number of uncertain elements. Further, Wallace (2000) has recently demonstrated how the basic concept of solution stability in parametric optimization tends to have very little to do with "real life" optimality in the actual problems where the parameters are uncertain.

To circumvent the difficulties in data availability and modelling methods, Huang et al. (1998) solved the municipal waste-flow allocation problem using a technique referred to as grey linear-programming (GLP). GLP is a method which can readily deal with interval input data and with the problems associated with the related methodologies mentioned earlier; namely the problem of solution stability. The solution output from GLP is a set of stable interval values for the objective function and for all decision variables. GLP is one component in the more general grey programming field that has been used extensively to solve several environmental management and planning problems operating under uncertain conditions (Huang, 1994, 1996; Huang et al., 1994a, 1994b, 1995, 1996a, 1996b, 1997; Chang & Wang, 1995; Chang et al., 1996; Yeh, 1996;Bass et al., 1997). In GLP, a given problem with interval parameters is transformed into two deterministic LP submodels which will guarantee stable upper and lower bounds for the desired objective-function values. However, unlike "normal" interval and best case-worst case analysis, this transformation is performed in a specifically prescribed order, depending upon the problem type, using an interactive algorithm that incorporates the output from the first submodel as input into the solution of the second submodel. Huang (1994) provides the extensive details of this algorithm and proves that GLP always produces stable solutions. Using GLP, Huang (1994) and Huang et al. (1998) provided a solution for Hamilton-Wentworth in which the existing system cost could be reduced by between \$200,000 to \$300,000 per year with only minor changes to the existing waste management scheme. In addition to the existing operating conditions, "what-if" solutions were provided for the hypothetical cases in which: (a) the incinerator was operated at its full capacity thereby reducing the longer term environmental impact of burying garbage in the landfill, and (b) the incinerator was closed completely thereby reducing its pollution impact upon the region's air quality.

In this paper, the application of a technique referred to as GAS is presented which combines a genetic algorithm (GA) with simulation (S) to determine "best" solutions to the problem of municipal waste flow allocation planning under uncertainty. For comparative purposes, the GAS study presented in the subsequent sections has been performed on the case data from Huang et al. (1998). The application of this type of solution approach has only recently been implemented (Pierreval & Tautou, 1997;Azadivar & Tompkins, 1999; Fontanili et al., 2000) and has never before been used for solid-waste planning. Since a genetic algorithm is incorporated within the solution process, a population of possible candidate solutions (i.e. possible settings for the decision variables) is maintained. For any given setting of the decision variables (i.e. for each candidate solution of the population set), GAS runs a simulation for all of the uncertain elements and the performance measure(s) (including the objective function) is/are determined from one - or a function of several - of the responses generated during the simulation phase. The results of the simulation phase are then compared for each of the candidate solutions and the genetic algorithm phase of GAS automatically evolves the system toward better solutions by generating a new candidate solution set to be evaluated in the subsequent simulation phase. Hence, for the first time, GAS permits the simultaneous incorporation of uncertainty directly within the optimization (or decision-making) phase for solid-waste planning. Furthermore, non-stable solutions are not retained by GAS in the population of candidate solutions, thereby eliminating this aforementioned difficulty.

Upon termination, GAS produces a best solution together with a family of several good solutions (i.e. the final population retained by the genetic algorithm component). Therefore, as with the method of Montano and Zandi (1999), GAS can also be easily used for policy planning comparisons. However, unlike the set generated solely by the genetic algorithm of Montano and Zandi (1999), all of the solutions in the population retained by GAS have been determined by a procedure that simultaneously incorporates uncertainty within the solution creation phase; not based solely on static settings for the data. Hence, GAS provides a means to overcome difficulties created by the earlier optimization procedures that do not directly include the uncertain components inherent in solid-waste systems. Should it prove desirable, each solution retained by the final population could be further studied via additional simulation analysis, with minor changes to parameter settings in a further "what if" evaluation phase. The "usability" of GAS has been greatly facilitated by the creation of a spreadsheet front-end, providing an easy, "natural" interface for the MSW planners in the municipality. Thus, end-users themselves can quickly create new MSW models and settings in a spreadsheet environment and further evaluate their impacts by either using GAS or simply running a Monte Carlo simulation on the proposed new settings. The spreadsheet format permits active end-user involvement, rapid prototyping and testing, and, most importantly, quick and easy performance of "what-if" analysis by the MSW managers for any proposed policy. In summary, GAS can be incorporated with the optimization framework to reflect uncertainties and thus permit the evaluation of alternative solutions for policy planning and analysis.

2. Modelling Formulation and Review of Previous Research

This section will provide a brief synopsis of the prior research into the MSW management problem in the Hamilton-Wentworth region; for more extensive details and actual source data the reader is referred to the original papers (Huang, 1994; Huang et al., 1998). The region covers an area of 1,100 square kilometers and includes six towns and cities; Hamilton, Dundas, Ancaster, Flamborough, Stoney Creek, and Glanbrook. 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, and the municipal budget for the MSW system within the region was set at $21,700,000. The region had constructed a system to manage these wastes. This system was comprised of the following components: a waste-to-energy incinerator facility called 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 blue-box recycling program contracted to and operated by the Third Sector Employment Enterprises; a household/hazardous waste depot, and; a backyard composting program (see Figure 1 in Huang et al., 1998). In the present system, each city and town retained responsibility for the collection of its own solid waste, while the municipality assumed responsibility for the treatment and disposal of the collected solid wastes received via its transfer stations and waste management facilities.

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, generates about 14,000,000 kilowatt hours per year of electricity which can be either used within the plant itself or sold to Ontario Hydro which is the provincial electrical utility. SWARU produces residual waste ash which must subsequently be transported to the landfill for disposal. It should also be noted that, due to their proximity to each other, SWARU and KTS can be viewed as essentially occupying the same municipal location.

The MSW management system within the region is a very complicated process and is further impacted by economic, technical, environmental, legislational and political factors. Prior to the GLP study, the municipality had not performed effective systematic planning for the flow of waste within the region and had not been able to effectively incorporate the inherent uncertain information within their planning processes. For the GAS study, the mathematical model to be presented differs somewhat from the earlier model used in GLP analysis. Specifically, the decision variables have been changed from variables designating "quantity" to variables corresponding to "proportions" of waste. This change, although not explicitly requisite, has been used to take full advantage of the benefits used in implementing GAS analysis and to more closely correspond to the "actual" decisions being made by the municipality. The notation employed is consistent with that of the GLP model, and permits a ready comparison between outputs from the two methods. However, in striving for this consistency between the two methods, a certain degree of redundancy in some of the model's constraints has been introduced.

In the GAS model, the various districts from which waste originates will be identified using subscript i; where i = 1, 2, …, 17 denotes the originating district. Table 1 provides the municipal area represented by each district number. The transfer stations will be 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 will be designated by x_{ij}, y_{jk}, and z_{ik} where x_{ij} represents the proportion of solid waste sent from district i to transfer station j; y_{jk} 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 $i = 1, 2, \ldots, 17$.

Table 1. Municipal Districts within the Hamilton-Wentworth Region and the Assigned District Numbers

Name of Municipal District	*District Number (i)*
Flamborough	1
Dundas	2
Hamilton 403 West	3
West Downtown Hamilton	4
Downtown Hamilton	5
East Downtown Hamilton	6
East Lower Hamilton	7
West Mountain Hamilton	8
East Mountain Hamilton	9
Lower Stoney Creek	10
East Mountain Stoney Creek	11
West Mountain Stoney Creek	12
Northeast Ancaster	13
Northwest Ancaster	14
South Ancaster	15
East Ancaster	16
Glanbrook	17

It had been noted that in the earlier GLP study, although several input parameters were uncertain, they had been estimated by the municipality's sold waste managers to fall within stated intervals. In this paper, if a data parameter A is estimated to lie within an interval, then the notation $\vec{A}$ will be used to represent this uncertainty. Now when the exact value of an item is not known, but is believed to lie within an interval [a, b], a standard Bayesian argument can be made that this value could be estimated by a random value generated from a Uniform distribution with minimum value a and maximum value b (Grey, 1995; Vaughan Jones, 1991). Hence, in the subsequent model, all such uncertain data values will be determined by randomly generating them from uniform distributions within their stated ranges; where the range was that used in the GLP study. Furthermore, should the "true value" or "true distribution" for these uncertain elements prove to possess more central tendencies within these intervals, then any statistical measures produced by GAS will actually tend to overestimate the true variance or true variability of these measures. Therefore, this Bayesian, uniform distribution assumption can also be considered as a very conservative assumption in this study.

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

The total transportation costs for wastes generated are:

$$T_1 = \sum_{i=1}^{17}\sum_{j=1}^{3}\vec{t}x_{ij}x_{ij}\vec{W}_i \tag{1}$$

$$T_2 = \sum_{i=1}^{17}\sum_{j=1}^{3}\sum_{k=1}^{3}\vec{t}y_{jk}y_{jk}x_{ij}\vec{W}_i \tag{2}$$

$$T_3 = \sum_{i=1}^{17}\sum_{k=1}^{3}\vec{t}z_{ik}z_{ik}\vec{W}_i \tag{3}$$

Equation (1) provides the transportation costs for waste flows from the districts (i.e. the cities and towns) to the transfer stations; equation (2) determines the total cost for transporting wastes from the transfer stations to the waste management facilities; equation (3) gives the costs for transporting wastes from the districts directly to the waste management facilities.

The costs for transporting residue created at SWARU (equation (4)) and the Third Sector (equation (5)) are:

$$T_4 = \left(\vec{t}sl\right)Q_2\sum_{i=1}^{17}\vec{W}_i\left[z_{i2} + \sum_{j=1}^{3}y_{j2}x_{ij}\right] \tag{4}$$

$$T_5 = \left(\vec{t}tl\right)Q_3\sum_{i=1}^{17}\vec{W}_i\left[z_{i3} + \sum_{j=1}^{3}y_{j3}x_{ij}\right] \tag{5}$$

where $\vec{t}sl$ is the cost per ton to transport waste from SWARU to the landfill, and $\vec{t}tl$ is the cost per ton to transport waste from the Third Sector to the landfill.

The total processing (or operating) costs for the waste management facilities are:

$$P_1 = \vec{\rho}_1\sum_{i=1}^{17}\vec{W}_i\sum_{k=1}^{3}\left[\vec{Q}_k z_{ik} + \sum_{j=1}^{3}x_{ij}y_{jk}\right] \tag{6}$$

$$P_2 = \vec{\rho}_2\sum_{i=1}^{17}\vec{W}_i\left[z_{i2} + \sum_{j=1}^{3}x_{ij}y_{j2}\right] \tag{7}$$

$$P_3 = \vec{\rho}_3\sum_{i=1}^{17}\vec{W}_i\left[z_{i3} + \sum_{j=1}^{3}x_{ij}y_{j3}\right] \tag{8}$$

where P_1 is the processing cost for the Glanbrook Landfill, P_2

is the processing cost for SWARU, and P_3 is the cost incurred for operating the Third Sector recycling facility.

The processing costs for transfer stations DTS, KTS and MTS are determined, respectively, by:

$$P_4 = \vec{\tilde{\delta}}_1 \sum_{i=1}^{17} x_{i1} \vec{\tilde{W}}_i \tag{9}$$

$$P_5 = \vec{\tilde{\delta}}_2 \sum_{i=1}^{17} \vec{\tilde{W}}_i \left[x_{i2} + \vec{\tilde{Q}}_3 \left\{ z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3} \right\} \right] \tag{10}$$

$$P_6 = \vec{\tilde{\delta}}_3 \sum_{i=1}^{17} x_{i3} \vec{\tilde{W}}_i \tag{11}$$

The revenue generated by SWARU (equation (12)) and by the Third Sector recycling facility (equation (13)) are:

$$R_2 = \vec{r}_2 \sum_{i=1}^{17} \vec{\tilde{W}}_i \left[z_{i2} + \sum_{j=1}^{3} x_{ij} y_{j2} \right] \tag{12}$$

$$R_3 = \vec{r}_3 \sum_{i=1}^{17} \vec{\tilde{W}}_i \left[z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3} \right] \tag{13}$$

Combining all of these elements produces the cost objective (equation (14)) as follows:

$$Minimize\ Cost = \sum_{p=1}^{5} T_p + \sum_{q=1}^{6} P_q - \sum_{r=2}^{3} R_r \tag{14}$$

This objective function must be optimized under various disparate restrictions that must be satisfied by the system modeled. The capacity limits for the transfer stations are:

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

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

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

where equations (15), (16), and (17) correspond to transfer stations DTS, KTS, and MTS.

The upper capacity limits placed upon the landfill, SWARU, and Third Sector are:

$$\sum_{i=1}^{17} \vec{\tilde{W}}_i \sum_{k=1}^{3} \left[\vec{\tilde{Q}}_k z_{ik} + \sum_{j=1}^{3} x_{ij} y_{jk} \right] \le \vec{\tilde{N}}_1 \tag{18}$$

$$\sum_{i=1}^{17} \vec{\tilde{W}}_i \left[z_{i2} + \sum_{j=1}^{3} x_{ij} y_{j2} \right] \le \vec{\tilde{N}}_2 \tag{19}$$

$$\sum_{i=1}^{17} \vec{\tilde{W}}_i \left[z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3} \right] \le \vec{\tilde{N}}_3 \tag{20}$$

Each facility must also satisfy constraints placed upon its lowest operating levels. The lower bound capacity limits for the transfer stations are:

$$\sum_{i=1}^{17} x_{i1} \vec{\tilde{W}}_i \ge \vec{K}_1 \tag{21}$$

$$\sum_{i=1}^{17} \vec{\tilde{W}}_i \left[x_{i2} + \vec{\tilde{Q}}_3 \left\{ z_{i3} + \sum_{j=1}^{3} x_{ij} y_{j3} \right\} \right] \ge \vec{K}_2 \tag{22}$$

$$\sum_{i=1}^{17} x_{i3} \vec{\tilde{W}}_i \ge \vec{K}_3 \tag{23}$$

The minimum capacity constraints for the waste management facilities (noting that there is no lower limit on the use of the landfill) are:

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

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

Equations (21) to (25) represent, respectively, the minimum operating capacity levels for DTS, KTS, MTS, SWARU, and the Third Sector.

The following are mass balance constraints to ensure that all of the waste generated is disposed of and that the amount of waste flowing into a transfer facility matches the amount flowing out of it:

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

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

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

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

$$\sum_{i=1}^{17} x_{ij} \vec{\tilde{W}}_i y_{j3} = \vec{R}W_j \sum_{i=1}^{17} x_{ij} \vec{\tilde{W}}_i \qquad j = 1, 2, 3 \tag{30}$$

Constraint (26) ensures the disposal of all the waste produced at a district. Recyclable waste disposal is established by constraint (27). In this determination, it is recognized that not all recyclable waste produced at a district is initially sent to the Third Sector recycling facility (i.e. some "blue box" waste may 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, the non-negativity constraints imposed upon the decision variables are:

$$x_{ij} \geq 0\,, \quad y_{jk} \geq 0\,, \quad z_{ik} \geq 0$$
$$i = 1, 2, \ldots, 17, \quad j = 1, 2, 3, \quad k = 1, 2, 3 \qquad (31)$$

Hence, the model presented for the Hamilton-Wentworth MSW problem is to optimize objective (14), subject to constraints (15) to (31). The major difference between this representation and the model of Huang et al. (1998) lies in the fact that the decision variables are now expressed as proportions and that they are also not designated as "grey" (or interval) values. This change reduces the total number of variables used in the GLP model by half. Furthermore, the uncertain parameters that had been expressed as interval data in Huang et al. (1998) have now been replaced by uniform probability distributions.

If this model did not contain uncertain elements, then it could be solved using some straightforward mathematical programming technique. When comparing two different solutions S1 and S2 (i.e. two different settings for the decision variables) in such a deterministic model, S1 would be considered a better solution than S2 if it produced a better result on the output variable of interest, Y. However, as with the "real world" application it represents, the model above does contain many uncertain elements. Hence, in order to compare any two solutions when these uncertain elements are present, it is necessary to compare some statistic of Y when S1 is modelled to the same statistic when S2 is modelled (Pierreval & Tautou 1997). These statistics are generated by simulation analysis performed on the solutions under consideration. Note that statistics can be simultaneously determined for several other measures of interest in addition to the objective function, permitting constraints on statistics of these measures to be directly incorporated into the model.

Therefore, in any proposed solution to the above model, a Monte Carlo simulation must be performed, randomly generating values for all of the uncertain elements. In the search strategy for the best solution to the problem, a population of candidate solutions is retained throughout the process. The comparative quality of these solutions is determined by the statistic calculated for their objective (i.e. the cost) and the surviving solutions during the "evolutionary" stage of the procedure are retained on a "survival of the fittest" basis. Since each of the solutions retained in this candidate population must satisfy all of the constraints, (15) to (31), the solutions produced by GAS will necessarily all provide stable solutions to the problem; thereby overcoming the difficulties outlined by Huang et al. (1998) and Wallace (2000).

The final solution produced by an evolutionary procedure can be influenced by the starting point of the search process. In the computational study, the GAS algorithm is started from the earlier GLP solutions and, thus, will never produce a worse solution than that of GLP. However, Yoogalingam (2001) has shown that solutions produced by GAS commencing at random starting points are entirely comparable to these solutions, but require slightly more solution time.

The evolutionary phase of genetic algorithms ensures that the search process does not become fixated at some local optima. Elements incorporated into the evolution steps consist of such things as population size, selection, mutation, and crossover (for more details see Falkenauer 1998, for example) and the exact procedure for the determination of the MSW settings are described in Yoogalingam (2001). Due to the heuristic nature of an evolutionary search and because of the inherent uncertainty within the problem structure, there can be absolutely no guarantee that GAS will provide the one, true optimal solution to the problem. However, the "real life" MSW application, itself, contains many uncertain components and so, in reality, would be most unlikely to even possess one "true" solution. Hence, although an argument could be made that GAS is, in fact, only a heuristic method, it must recognized that the MSW problem contains considerable uncertainty and, if not solved using an approach directly incorporating this uncertainty, how else could a solution to realistically satisfy this problem be determined? In summary, the actual MSW problem, itself, contains many sources of uncertainty that must be accounted for in the decision making phase, and GAS readily incorporates these uncertainties directly into its solution process. As will be shown subsequently, by adopting such an approach, the GAS algorithm produces good solutions to the MSW problem.

3. Scenario Testing for the GAS Model

It had been mentioned earlier that the MSW managers of Hamilton-Wentworth were interested in a technique which (a) could determine whether or not their existing approach provided the best solution to the MSW management problem, (b) could produce a better solution where possible, and (c) would readily permit analysis of alternative hypothetical situations. The GAS method can be used for all three of these purposes. In order to examine how well GAS performs in planning for solid waste management, several different scenarios of interest were considered under a number of different parameter settings. Three of these cases had appeared in the earlier GLP study of Huang et al. (1998), while the fourth case has not been considered previously. Hence, the GLP study can be used as a basis of comparison for the performance of the GAS approach.

Since SWARU, the waste-incineration facility, has been the focus of intense environmental and operational scrutiny, each scenario revolved around certain aspects of the operations of this facility. There are several reasons for such scrutiny surrounding SWARU. Based upon concerns related to air-quality and pollution, there has tended to be a great deal of public anxiety and opposition to most forms of waste incineration. In addition to the public pressure, the Ontario Ministry of the Environment has established a moratorium on the creation of new incineration facilities and has considered introducing further restrictions on the operations of all existing incinerators. Hence, should any new legislated restrictions become enforced, SWARU's operations might have to be curtailed, forcing the municipality to quickly devise alternate plans for its MSW processing. From a budgetary perspective, incineration is a relatively more expensive process in comparison to landfilling. Therefore, from a cost standpoint, incineration provides a less desirable means of disposal. Given the public pressure on governments to reduce taxation, landfilling provides a more attractive disposal option than incineration. Conversely, incineration is more environmentally desirable than landfilling in that the waste is essentially "eliminated" immediately (the only residue produced is the resulting ash) and, therefore, will not create the same sort of potential, long-term environmental hazard posed by "raw" (or un-incinerated) waste buried in a landfill. A further benefit of incineration is that it dramatically reduces the space requirements for valuable municipal land that would necessarily be devoted to a noxious, landfill facility.

SWARU currently operates at a level which is lower than its designed capacity. Scenario 1 examines the case where SWARU continues to operate at this current capacity level. Hence, the solution to this scenario can be compared directly to the way in which the municipality presently performs solid waste management. Scenario 2 looks at what would happen if SWARU were operated at it maximum designed capacity. This solution would be for the case in which it was decided that the municipality would landfill as little waste as possible; thereby freeing up land for other purposes and reducing the long-term environmental problems associated with landfilling waste. Scenario 3 studies the possible situation in which SWARU can operate anywhere in the range from being closed completely up to operating at its maximum capacity. Hence, the solution to this scenario could be considered the best overall solution possible for the MSW problem. Scenario 4 considers the very real possibility that SWARU would be closed completely due to legislated requirements. In this situation, all non-recycled solid waste would necessarily be sent to the landfill for disposal. Note that if the cost of incineration was found to be prohibitively high, then the solutions produced under Scenarios 3 and 4 would be identical. GLP solutions for Scenarios 1, 2, and 4 appear in Huang et al. (1998).

With these four scenarios established, it then becomes necessary to run computational experiments for the MSW system operating under the conditions as outlined under each scenario. This experimentation is not as straight forward as it might initially appear. In the GLP experimentation (Huang, 1994; Huang et al., 1998), the decision variables were the waste flows for the different waste-delivery routes, the constraints mainly revolved around capacity restrictions on various facilities, and the objective was to achieve the allocation of waste flow through the system with the minimum cost. Aside from the algorithmic details required to maintain stable solutions (Huang 1994), the underlying problem formulation was a basic linear programming (LP) problem.

Under GAS, the problem formulations may be structured in many different ways that would not be permissible with LP. For instance, since a genetic algorithm's solution time and accuracy are essentially not dependent upon the nature of the variables used, the decision variables employed in the problem could just as easily be formulated as continuous, integer, or mixed variables. Each of these decision variable settings has been examined in extensive pre-testing of GAS (Yoogalingam, 2001). More importantly than the type of decision variable used (or more different from standard LP formulations), a simulation is performed for each setting of the possible decision variables being considered in the solution search process. Therefore, unlike LP which requires hard constraints for its solution, GAS permits the additional possibility that the constraints can be formulated for statistics and/or percentiles of values of interest. Hence, GAS essentially permits the possibility that all constraints are, in fact, "soft" constraints. Recognizing the practical implications (Foulds & Thachenkary, 2001) of this relaxation (for instance, a waste handling facility would very likely be capable of handling a minor violation of a stated quantity limit), several of the hard constraints from the original GLP model have been formulated as percentiles which allowed them to be violated by a solution setting 0.05% of the time; unless stated otherwise.

Furthermore, although the GAS model is structured to minimize the "cost" of the system, since a simulation is performed for each decision variable setting then, as with the constraints, this cost could also be measured in many different ways. In the analysis of results presented in the subsequent section, the GAS problem has been structured according to the approach outlined in the following way. Although several possible permutations of problem formulations have been considered extensively (Yoogalingam, 2001), only a relevant subset of these possibilities is chronicled in this paper. In order to provide a broad examination of the possible solutions, five different cost objectives were tested for each scenario. The objectives considered were to minimize (i) the mean cost, (ii) the standard deviation of the cost, (iii) the maximum cost, (iv) the 95th percentile of the cost, and (v) the range (= maximum – minimum) of the cost. Moreover, regardless of which of these cost statistics was actually used for the objective function measure, the resulting values for each of the other statistics determined by that solution would also be calculated and recorded.

Each objective measure proposed above has distinct practical benefits accompanying it and provides meaningful results for the municipality. To minimize the mean would provide a solution that, for all possible waste flow allocation patterns within the municipality, would produce the solution that had the lowest cost on average. Although a solution minimizing the mean cost would be quite practical over the long term, municipalities tend to be quite risk averse to anything which could possibly overspend their stated budget value. This is due to the fact that municipal budgets provide fixed annual dollar amounts to cover various programs. Recognizing that the total annual cost will follow some form of distribution because of all the uncertain components contained in its evaluation, the minimum and maximum possible costs could, in fact, be far different from the mean cost found. Hence, to find the solution which minimizes the maximum possible cost would satisfy the risk aversion characteristics of a municipality. Such a solution might have a relatively large cost on the average, but would guarantee that the amount spent would never be higher than the amount stated. This clearly has distinct advantages for any municipality that must prepare annual budgets and fund its programs through taxation; in planning for the worst case, spending less than the budgeted amount would be far more politically acceptable than being forced to spend more. Minimizing the 95th percentile of the annual cost provides similar benefits to that of minimizing the maximum cost; namely, it establishes a bound on the amount (albeit a soft upper bound) that would be spent by the municipality. In general, the nature of this solution would provide a relatively low upper value for the total cost, while perhaps not sacrificing all "practicality" in trying to minimize what might prove to possibly be a very remote, true maximum value at the expense of more likely lower values. The range and the standard deviation of the total cost both provide objectives which attempt to reduce the variability of the costs. These objectives are practical from the municipality's standpoint, since they both attempt to reduce the variation experienced in the distributions of the total annual cost. This is important from a budgetary perspective, since by reducing this variability, the solution provided is much more likely to be closer to the actual solution experienced than any other solution (i.e. they reduce the risk). Hence, it will be much more likely to be closer to the planned for (and hence budgeted for) solution than any other solution suggested. Therefore, by using this objective/approach, the municipality would be able to claim that its budgeted solution would be very close to the actual outcome experienced, justifying the solution approach taken and exemplifying the concept of risk aversion.

4. Analysis of Results

The four scenarios discussed in the previous section were each examined using GAS applied to the variations of the problem settings. These solutions were then compared with respect to the GLP solutions determined in the earlier study and to the solution currently employed by the municipality. The GAS analysis was further supplemented by subsequent simulation studies of the solutions found. Table 2 provides a summary of the annual costs determined for the three scenarios that the earlier GLP study had examined and for solution currently employed by the municipality. Since the GLP method had been used for deriving these values, all the figures are stated as a range between the minimum and maximum costs possible under each particular setting. As can be observed from this table and as reported in Huang et al. (1998), the GLP solution improves upon the existing solution by a reduction in total annual system costs ranging between \$200,000 and \$300,000.

The results for the GAS analysis for the system operating under the disparate conditions specified by Scenarios 1 to 4 are presented in Tables 3 to 6. Five separate problems, corresponding to the five different objective functions described in the previous section, are solved for each scenario. Column 1 in each table shows the objective function that was minimized in the respective problem. Each row of the table then provides the statistical values calculated for the best solution when the objective specified in column 1 was optimized. Within the numerical data for each column in each of the tables, the bold-faced number represents the best value found for that particular measure. For example, the second column in Table 3 shows the mean annual cost found for the best solutions to each of the 5 separate problems solved for Scenario 1. The second row, corresponding to the problem of minimizing the mean annual cost, shows that the best mean cost determined was \$17,439,618. However, the solution found when the 95th percentile of the annual cost was optimized has a mean annual cost of \$17,354,376; or a mean value which is, in fact, lower than the value found when the mean cost is the minimized objective function. This type of outcome can be readily observed to occur frequently in all of the problems under each scenario. Although initially this may appear contradictory, it is neither a paradoxical nor unexpected result. What this illustrates is that the evolutionary nature of genetic algorithms does not guarantee solutions which are globally optimal for a particular problem and that this may be especially true when these problems, themselves, contain many uncertain compo-

Table 2. Annual Costs (in millions of \$) for the Existing MSW System in Hamilton-Wentworth and the Published GLP Solutions

Solution Source	SWARU Operation Setting	Scenario Number	Minimum Cost	Maximum Cost
Existing Solution	Operating at Current Capacity	1	15.2	21.0
GLP Solution	Operating at Current Capacity	1	15.0	20.7
GLP Solution	Operating at Maximum Capacity	2	16.3	22.4
GLP Solution	Incinerator Facility Closed	4	13.7	18.5

nents.

A closer examination of the results for Scenario 1 (see Table 3), the case in which SWARU continues to operate within its existing capacity ranges, indicates that the best values for the annual cost will be a mean of \$17.3 million, a standard deviation of \$1.75 million, a maximum of \$20.5 million, a 95th percentile of \$20.2 million, and a range of \$6.0 million. The best mean value was found in the problem minimizing the 95th percentile with three of the other problems producing very similar solutions. The problem in which the maximum annual cost was minimized produced the best values for all other measured statistics (i.e. the best values for the standard deviation, minimum, maximum, range, and 95th percentile). In fact, other than for the standard deviation objective, all objectives provided very similar values for all of the measured statistics. A detailed examination of their decision variables, indicated that all four of these objectives produced very similar waste allocation solutions.

Since GLP specifies its results as a minimum-to-maximum interval, it is interesting to examine the minimum and maximum values for the problems considered. Again, except for the standard deviation objective, the four other objectives all provided [minimum, maximum] solution intervals in the range of approximately \$[14.5, 20.5] million; with the best solution produced by the maximum objective. The GLP solution found for this scenario had annual costs in the interval of \$[15.0, 20.7] million. Hence, GAS has provided a solution which is \$[0.5, 0.2] million better than this GLP solution or stated another way, an improvement of \$200,000 to 500,000 per year (see Table 7). An examination of the allocation decision variables produced by GAS indicated that this improvement could be implemented with only minor changes to the waste disposal scheme proposed by GLP. Now the existing waste allocation system in the municipality had a cost range of \$[15.2, 21.0] million and Huang et al. (1998) had shown that only slight changes to this scheme were required in order to implement their GLP solution. Similarly, therefore, with only minor changes to the existing allocation system, the GAS solution provides a savings of \$500,000 to 700,000 per year to the MSW allocation system currently employed by the municipality of Hamilton-Wentworth.

For the case in which SWARU must increase its operating level up to its maximum capacity range (Scenario 2), an examination of the output (see Table 4) indicates that the best values for the annual cost will be a mean of \$18.7 million, a standard deviation of \$1.8 million, a maximum of \$22.1 million, a 95th percentile of \$21.7 million, and a range of \$6.5 million. The problem in which the mean annual cost was minimized produced the best values for all measured statistics. Other than for the range objective, all objectives provided very similar values for all of the measured statistics and an examination of their solutions showed that all of these objectives produced similar waste allocation solutions. The GAS solution found for this scenario had annual costs in the interval of [\$15.6 million, \$22.1 million], while GLP produced costs in the range of \$ [16.3, 22.4] million. Hence, GAS has provided an improvement of \$300,000 to 700,000 per year over that found by GLP (see Table 7).

In Scenario 3, SWARU is permitted to operate at any capacity level, from being closed completely up to its maximum capacity. In effect, the solutions to this scenario are the best possible overall solutions to the MSW problem. The output from the computational experimentation (see Table 5) indicate that the best values for the annual cost will be a mean of \$15.9 million, a standard deviation of \$1.5 million, a maximum of \$18.7 million, a 95th percentile of \$18.4 million, and a range of \$5.2 million. The problem in which the maximum annual cost was minimized produced the optimal values for the mean, maximum, and 95th percentile, while minimizing the 95th percentile objective provided the best values for the range and standard deviation. Only the range objective produced a solution which was very different from those of the other objectives. GLP was not tested on Scenario 3. However, the GAS solution found for this scenario has annual costs in the interval of \$[13.4, 18.7] million. For comparative purposes, this MSW disposal scheme is \$1,600,000 to 2,000,000 per year lower than the solution currently being employed by the municipality (see Table 7) and is also \$1,100,000 to 1,800,000 per year lower than the best GAS solution found when SWARU operates at its current capacity level. Hence, this solution indicates that significant cost savings could be achieved if the municipality were to change their usage of the incinerator. Furthermore, although incineration at SWARU has a relatively high cost for waste disposal, this solution indicates that it is, in fact, cheaper overall to continue to use this method than to landfill all of the waste entirely. This would most likely be due to the transportation costs involved.

When the SWARU incineration facility is closed completely (Scenario 4), the computational experimentation indicates (see Table 6) that the best values for the annual cost will be a mean of \$16.0 million, a standard deviation of \$1.3 million, a maximum of \$18.5 million, a 95th percentile of \$18.2 million, and a range of \$4.8 million. Other than for the range objective, all other objectives provided identical waste allocation solutions. The GAS solution found for this scenario had annual costs in the interval of \$ [13.7, 18.5] million, as did the GLP solution (see Table 7). An examination of the decision variables indicated that, since all waste collected had to be disposed of at the landfill, both GAS and GLP produced identical solutions for this scenario. That is, when SWARU is closed, there are virtually no alternative courses of action to consider. It is interesting to compare this solution to that found in Scenario 3. The minimum value in this scenario is \$300,000 higher than that in the previous scenario. However, the maximum value in this scenario is actually \$200,000 lower than that in Scenario 3. It can be observed that while the solution to Scenario 3 provides a lower cost on the average and better cost values at the lower end of the cost spectrum, it does not dominate Scenario 4 at the higher end of the cost spectrum. Hence, depending upon how one characterizes the municipality's evaluation of land resources consumption, it may, in fact, be better from a cost standpoint to close the SWARU facility completely.

Table 3. Scenario 1, SWARU must be Operated within its Existing Operating Level Ranges

Objective Minimized	Mean	Standard Deviation	Minimum	Maximum	Range	95th Percentile
Mean	17,439,618	1,759,594	14,515,592	20,612,332	6,096,740	20,271,235
St. Dev.	19,031,954	1,827,478	15,991,612	22,322,300	6,330,688	21,647,953
95th Percentile	17,354,376	1,758,365	14,506,388	20,597,668	6,091,280	20,256,814
Maximum	17,424,693	1,758,208	14,503,476	20,594,184	6,090,708	20,253,437
Range	17,507,793	1,767,534	14,571,180	20,694,232	6,123,052	20,351,527

Table 4. Scenario 2, SWARU must be Operated within its Maximum Operating Capacity Range of [2500, 2700] Tons per week

Objective Minimized	Mean	Standard Deviation	Minimum	Maximum	Range	95th Percentile
Mean	18,728,213	1,895,877	15,583,339	22,151,030	6,567,691	21,782,050
St. Dev.	18,761,902	1,899,955	15,610,458	22,192,277	6,581,819	21,822,409
95th Percentile	18,734,977	1,896,656	15,588,843	22,159,233	6,570,390	21,790,081
Maximum	18,753,070	1,898,872	15,603,300	22,181,365	6,578,065	21,811,709
Range	20,256,510	1,966,199	16,992,141	23,803,427	6,811,286	23,421,598

Table 5. Scenario 3, SWARU may me Operated anywhere in the Range between being Closed Completely up to its Maximum Operating Capacity, i.e. between 0 and 2700 Tons per week

Objective Minimized	Mean	Standard Deviation	Minimum	Maximum	Range	95th Percentile
Mean	16,456,603	1,638,601	13,728,573	19,404,852	5,676,279	19,088,919
St. Dev.	16,937,108	1,697,368	14,114,133	19,994,039	5,879,906	19,665,919
95th Percentile	16,350,603	1,526,973	13,800,736	19,090,247	5,289,511	18,798,078
Maximum	15,984,701	1,536,909	13,418,979	18,742,845	5,323,866	18,448,589
Range	18,190,511	1,722,511	15,318,690	21,285,607	5,966,917	20,954,694

Table 6. Scenario 4, SWARU is Closed Completely

Objective Minimized	Mean	Standard Deviation	Minimum	Maximum	Range	95th Percentile
Mean	16,093,464	1,386,048	13,747,935	18,548,294	4,800,359	18,292,629
St. Dev.	16,093,464	1,386,048	13,747,935	18,548,294	4,800,359	18,292,629
95th Percentile	16,090,909	1,386,048	13,747,935	18,548,294	4,800,359	18,292,629
Maximum	16,090,909	1,386,048	13,747,935	18,548,294	4,800,359	18,292,629
Range	17,745,441	1,455,859	15,281,396	20,323,588	5,042,192	20,055,887

Table 7. Comparison of Annual Costs (in millions of $) between the Published GLP Solutions and the Best GAS Solutions

Scenario Number	SWARU Operation Setting		GLP Solution	Best GAS Solution Found	Difference Between GAS & GLP
1	Operating at Current Capacity	Min	15.0	14.5	0.5
		Max	20.7	20.5	0.2
2	Operating at Maximum Capacity	Min	16.3	15.6	0.7
		Max	22.4	22.1	0.3
3	Between 0 & Maximum Capacity	Min	N/A	13.4	1.60*
		Max	N/A	18.7	2.00*
4	Incinerator Facility Closed	Min	13.7	13.7	0.0
		Max	18.5	18.5	0.0

* Difference measured in comparison to the GLP solution for the existing municipal solid waste management operations in the Municipality of Hamilton-Wentworth.

Overall, this scenario analysis has produced several interesting results with respect to MSW disposal planning. In summary, the experimentation has demonstrated the value of considering several different approaches, or objectives, within each scenario. In general, all of the objective functions considered for the various scenarios tended to produce quite similar results, although no single objective consistently dominated all of the others. Minimizing the maximum annual cost has tended to provide very good solutions for all of the tested scenarios. The relatively poorest performing objectives were the two which strove to reduce the variability (or financial risks) of the costs; namely the range and the standard deviation. Upon reflection, such a finding should not have been unexpected, since these objectives would sacrifice the concept of low costs in order to keep variability to a minimum. Therefore, if these objectives are to be considered for future analysis, then they should include additional constraints to keep the total costs beneath certain targeted amounts. The experimentation has demonstrated that GAS can produce better solutions to GLP. This may be due, in part, to the fact that GAS need not focus exclusively on the extreme value ranges, but can also consider intermediate values and statistics of measures such as means and percentiles. Another reason for this could perhaps be due to the constraint relaxation introduced. In doing so, hard constraints can be easily (and realistically) relaxed in such a way that improved solutions can be readily determined. Irrespective of the reasoning, it has been demonstrated that GAS can be used to find an MSW allocation solution which could be almost $2,000,000 lower than that currently being used in the municipality, and could therefore save approximately 10% from the annual MSW budget.

5. Additional Experimentation and Analysis

After the initial analysis of the four scenarios described in the preceding section, certain subsequent experimentation could be deemed necessary. Each scenario had focused upon some aspect regarding the use of the incinerator. Regardless of the actual solution implemented by the municipality (found using GAS or any other method), SWARU use would necessarily follow some form of distribution given the multitude of uncertainties comprising the MSW system. What the distribution of this facility-use actually looked like for a particular solution would hold considerable practical interest to the MSW planners. If the best solutions are implemented for Scenarios 1 to 3 (those shown in Table 7), then a simulation of the use of SWARU can be easily run on the same GAS models used to find the respective solutions. The resulting distributions of SWARU use for these solutions are shown in Figures 1 to 3. Clearly, in Scenario 4, there will be no use of the SWARU incinerator and therefore no distribution.

For Scenario 1 in which SWARU continues to operate within its existing capacity range, Figure 1 shows that the weekly use of the incinerator will tend to follow a relatively symmetrical distribution pattern. For Scenario 2, where SWARU operates within its maximum capacity range, the incinerator use again tends toward a relatively symmetrical distribution pattern within the lower end of its permissible range (Figure 2). However, the distribution also appears to be somewhat skewed toward the lower limit. In order to attain low overall system costs under the requirement that the expensive incinerator operates at high capacity, the best solution has attempted to keep costs down by operating SWARU at the lower end of the permissible range. In Scenario 3, SWARU may operate at any feasible capacity level. Figure 3 illustrates the somewhat triangular-shaped use-distribution found for the best solution under this scenario. Although the incinerator is expensive, the distribution pattern clearly shows that the incinerator should be used even though the actual levels that it operates at are considerably beneath its current operating level. Furthermore, in no case does this solution indicate that SWARU is never used.

Since SWARU is an expensive facility to operate, it was of interest to see what effect a permissible reduction in its use would have on the system costs and allocations for the various scenarios. Hence, for Scenarios 1 and 2, the capacity constraints were relaxed to permit a violation on their limits up to 10% of the time.

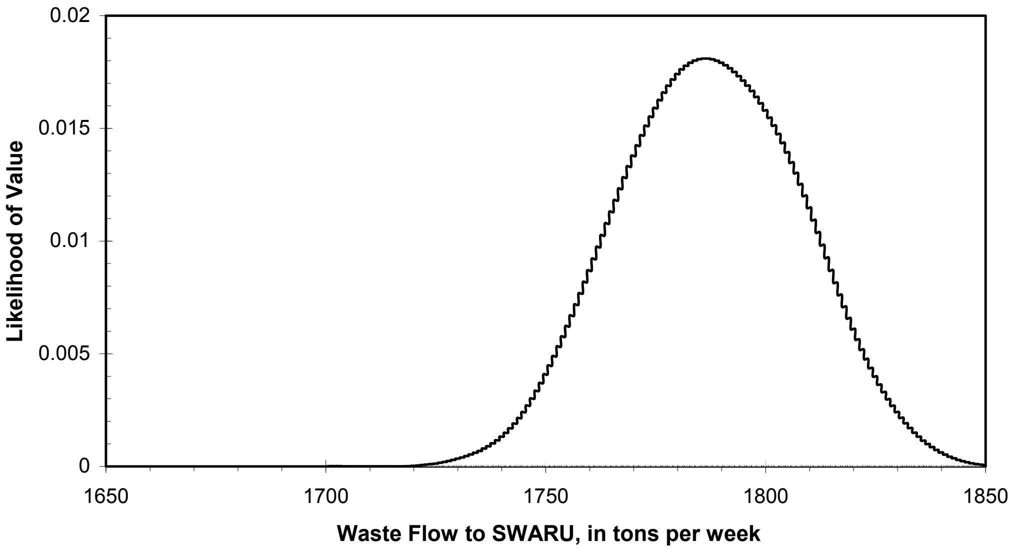

Figure 1. Scenario 1: weekly distribution, in tons per week, of SWARU use for the best solution found when it must be operated within its maximum operating capacity range of [2500, 2700] tons per week, but may violate this requirement 10% of the time.

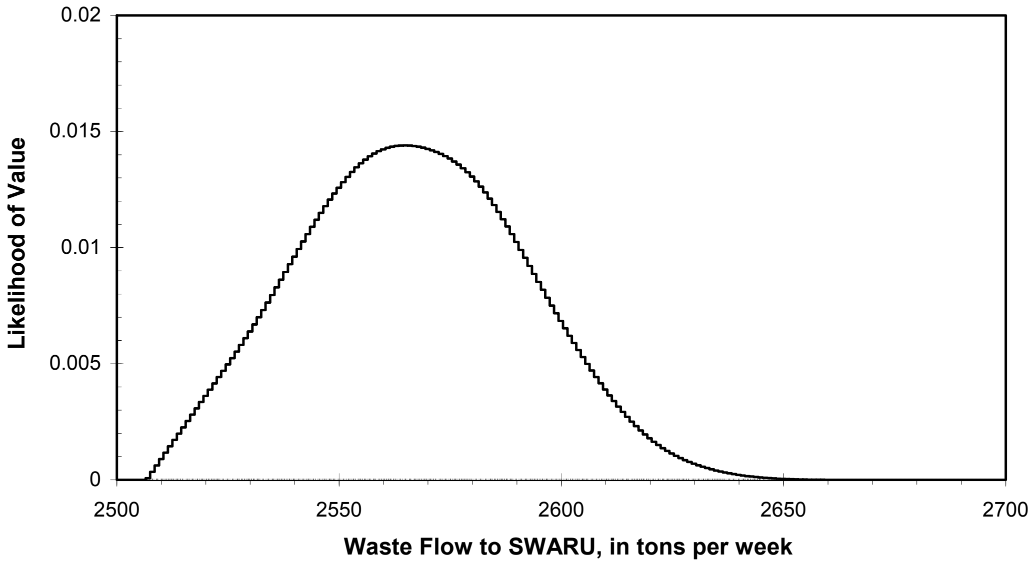

Figure 2. Scenario 2: Weekly distribution, in tons per week, of SWARU use for the best solution found when the incinerator must be strictly operated within its maximum operating capacity range of [2500, 2700] tons per week.

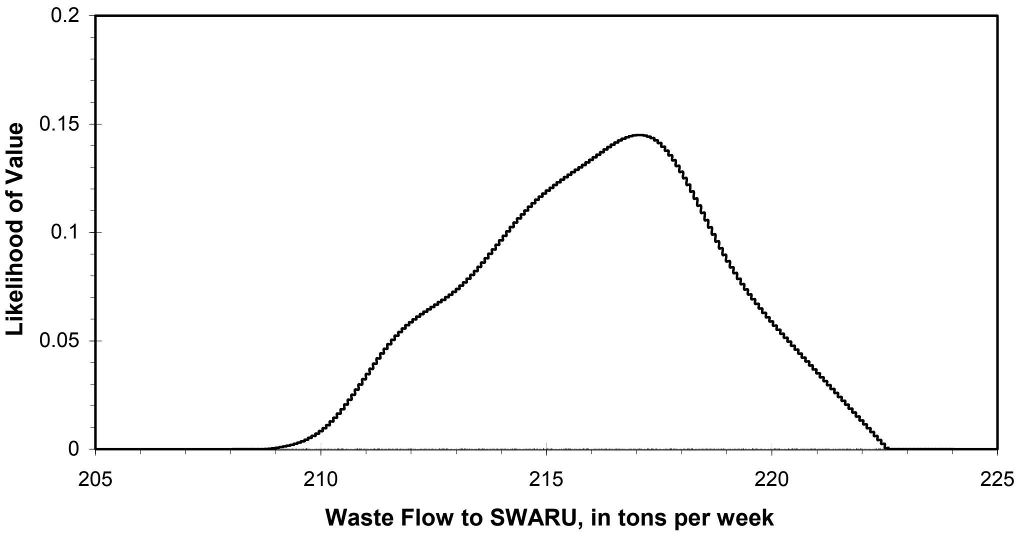

Figure 3. Scenario 3: weekly distribution, in tons per week, of SWARU for the best solution when the incinerator can be operated anywhere from being closed up to its maximum operating capacity.

Obviously such a relaxation would have no impact on the solutions for Scenarios 3 and 4. Table 8 shows the results obtained under Scenario 1 for the five objectives in the case where SWARU must be operated within its existing capacity ranges, with an allowance of their being operated outside this range 10% of the time. Each of the objectives produced virtually identical values for all measured statistics, while the problem minimizing the 95th percentile of the annual cost actually produced the best values. The table indicates that the best values for the annual cost will be a mean of $17.3 million, a standard deviation of $1.75 million, a maximum of $20.5 million, a 95th percentile of $20.2 million, and a range of $6.0 million. Although the values in Table 8 are very similar in magnitude to those shown in Table 3, a closer examination reveals that each measure of cost is, in fact, about $50,000 lower. Since the SWARU constraints have been relaxed, this result could be expected, although the actual amount of this reduction would not be obvious a priori. Figure 4 shows the weekly distribution of use at SWARU from a simulation of the best solution found in Table 8. The solid bar included in the figure shows the current minimum weekly operating capacity for SWARU. The figure shows that this minimum is violated and results from the simulation indicated that this violation occurs at the maximum permissible level of 10%. Hence, in order to reduce total system costs, operation of the incinerator at a lower level than its current minimum operating capacity is necessary.

Table 9 indicates the results obtained for Scenario 2 when SWARU operates at its maximum capacity but may violate this restriction up to 10% of the time. Once again, each objective function produced essentially identical values for all measured statistics. However, the problem of minimizing the mean annual cost produced the best values of each measure for this case. Table 9 shows that the best values for the annual cost will be a mean of $18.6 million, a standard deviation of $1.89 million, a maximum of $22.0 million, a 95th percentile of $21.7 million, and a range of $6.5 million. As with the previous case, the values in Table 9 are of similar magnitude to those in Table 4, but are lower by $10,000 to $100,000 depending upon the measure examined. Figure 5 shows the weekly distribution of SWARU operation obtained by simulating the best solution from Table 9. The solid bar in the Figure 5 shows the lower bound for the (current) maximum weekly operating capacity for SWARU. The figure shows a clear violation of this lower bound and the simulated results indicate that this violation occurs at the maximum permissible level of 10%. Hence, once again, it can be demonstrated that in order to reduce the total system costs, the incinerator would have to be operated at a lower level than its currently specified lower bound.

Although there are many ancillary elements that could be produced for supplementary analysis of the MSW problem, the final element to be presented concerns the total annual costs necessary to run the entire solid waste system.

While the costs and operating details of SWARU would prove to be of distinct interest to the MSW planners, the nature of the total system costs has a more direct impact upon a diverse group of planners within the municipality. Specifically, with respect to budgetary details, it is of strategic importance for municipal planners to be able to reasonably assess the risk attached to budget allocations made for various programs within the municipality (one such program being MSW management). That is, it is of considerable importance to assess how likely the amount budgeted for solid waste management will prove insufficient to cover the amount actually necessary to implement the system. Conversely, planners would also be interested in assessing how likely the budgeted

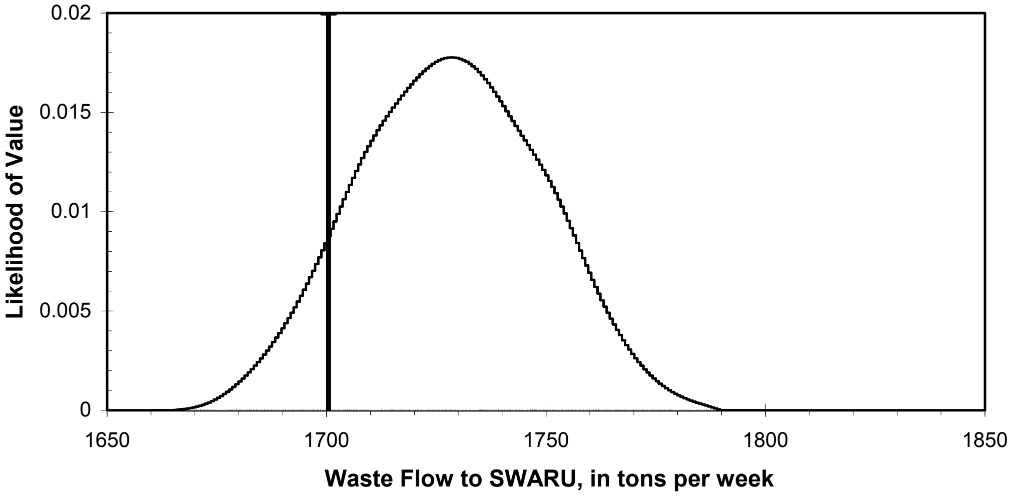

Figure 4. Scenario 1: weekly distribution, in tons per week, of SWARU use for the best solution found when the incinerator must be operated within its existing operating level ranges, but may violate these requirements 10% of the time.

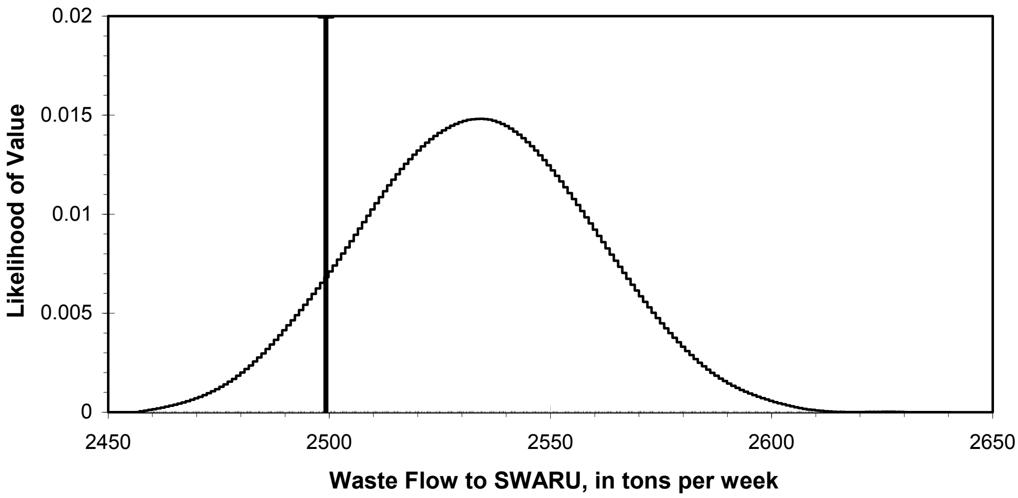

Figure 5. Scenario 2: weekly distribution, in tons per week, of SWARU use for the best solution found when it must be operated within its maximum operating capacity range of [2500, 2700] tons per week, but may violate this requirement 10% of the time.

Table 8. Scenario 1, SWARU must be Operated within its Existing Operating Level Ranges, with the Allowance of Violating these Requirements 10% of the Time

Objective Minimized	Mean	Standard Deviation	Minimum	Maximum	Range	95th Percentile
Mean	17,415,192	1,756,656	14,496,592	20,581,497	6,085,045	20,241,260
St. Dev.	17,435,085	1,758,633	14,512,975	20,605,158	6,092,183	20,264,365
95th Percentile	17,386,810	1,753,483	14,473,317	20,547,670	6,074,353	20,207,845
Maximum	17,413,897	1,756,191	14,495,956	20,579,688	6,083,732	20,239,324
Range	17,450,308	1,759,966	14,525,732	20,622,525	6,096,793	20,281,524

Table 9. Scenario 2, SWARU must be Operated within its Maximum Operating Capacity Range of [2500, 2700] Tons per week, with the Allowance of Violating this Requirement 10% of the Time

Objective Minimized	Mean	Standard Deviation	Minimum	Maximum	Range	95th Percentile
Mean	18,685,334	1,890,658	15,548,845	22,098,451	6,549,606	21,730,511
St. Dev.	18,686,646	1,891,051	15,549,568	22,100,537	6,550,969	21,732,555
95th Percentile	18,693,792	1,891,453	15,555,991	22,108,352	6,552,361	21,740,237
Maximum	18,689,046	1,891,140	15,551,911	22,103,188	6,551,277	21,735,129
Range	18,687,791	1,890,916	15,550,999	22,101,501	6,550,502	21,733,541

amounts could be reallocated to other programs, should they remain unspent; or even how likely it would be for the occurrence of any particular system cost. This is exactly the type of information that can be produced by GAS solutions and by subsequent simulation studies of any solution settings. Considerable information concerning cost values together with their corresponding likelihoods of occurrence can be produced to support this planning process. It should be noted that GLP also provides this type of information, but on a significantly smaller scale. The outputs produced in GLP are the minimum and maximum possible values for the annual system costs (GAS also provides this information). However, these extreme values are presented without any information on the likelihoods of their occurrence, let alone the likelihoods of any intermediate values falling within their stated range.

In order to demonstrate one approach to the presentation of cost information, Figures 6 to 9 show the respective distributions of the annual system costs for the best solutions to Scenarios 1 to 4. These distributions actually represent “extreme” likelihoods, since all of the probability distributions within each scenario model have been set up to be perfectly correlated with each other. The distributions are extreme in that when the waste quantity generated for one district is high(/low), the wastes generated at every other district are also high(/low), all costs generated are also high(/low), and all revenues generated are low(/high).

Hence, in Figures 6 to 9, when costs are high, they are very high and when costs are low, they are very low. The values and likelihoods shown in these figures provide extremely conservative estimates and, since it is very unlikely that all of the distributions would be perfectly correlated with one another, they could be considered as results from a type of best-case/worst-case analysis for possible cost distributions. Should any additional information become available regarding correlations between uncertain items in the model, then subsequent simulations of the various scenarios could be performed. Otherwise, it could be assumed that the variability shown by each of the distributions is biased upward and, therefore, that the figures provide a worst-case analysis for the cost likelihoods. However, under the assumption that perfect correlations could occur, the values at the extreme minimum and maximum costs in the figures could in all likelihood occur under each of the scenarios considered. Therefore, the municipality would be well-advised to plan on the basis of the occurrence of these minimum and maximum annual costs and must construct their budget plan accordingly.

This type of information on likelihoods of outcomes is not provided when only basic best-case/worst-case value estimates are given.

6. Summary and Conclusions

This study has provided many advances to the planning problems of collection, allocation and disposal of municipal solid waste. For the first time, a GAS solution approach has been employed in solid waste planning. GAS has extended the earlier GLP research used in both operational and strategic planning analysis. Although these concepts have been applied explicitly to the solid waste planning problem in the munici-

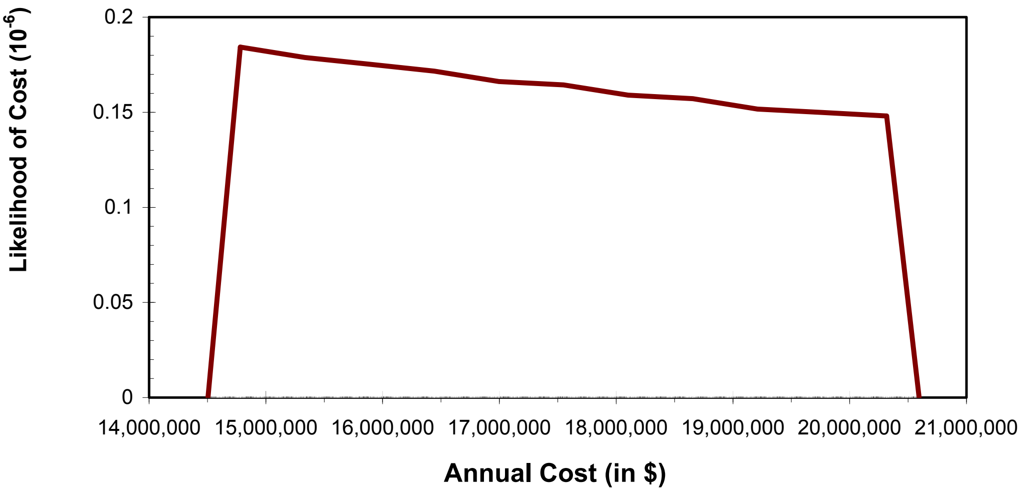

Figure 6. Scenario 1: distribution of annual costs for the best solution found when SWARU is operated within its existing operating level ranges.

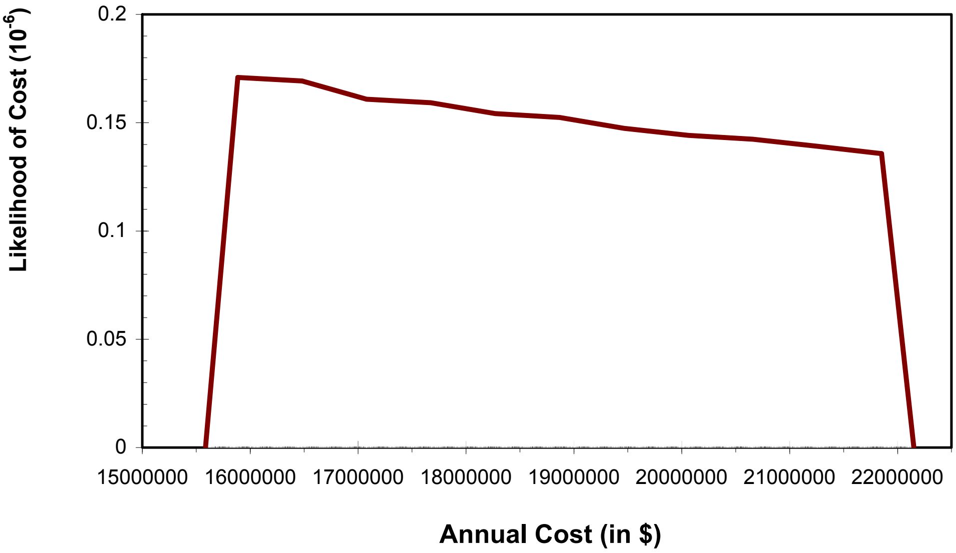

Figure 7. Scenario 2: distribution of annual costs for best solution when SWARU is operated within its maximum operating capacity range of [2500, 2700] tons per week.

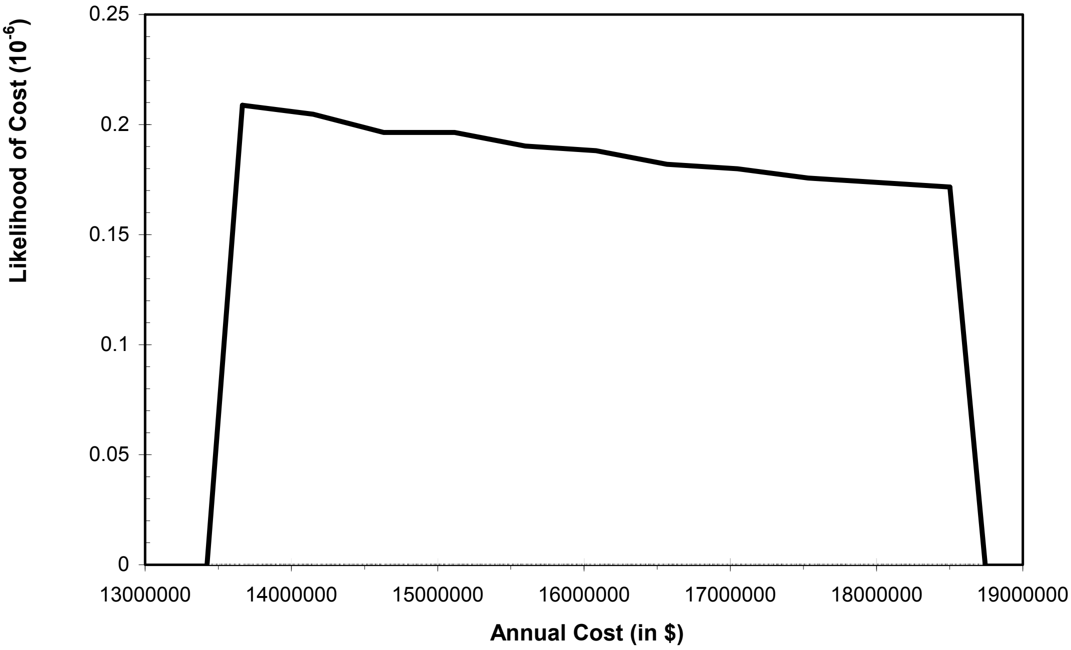

Figure 8. Scenario 3: distribution of annual costs best solution when SWARU is operated anywhere in the range between being closed completely up to its maximum operating capacity.

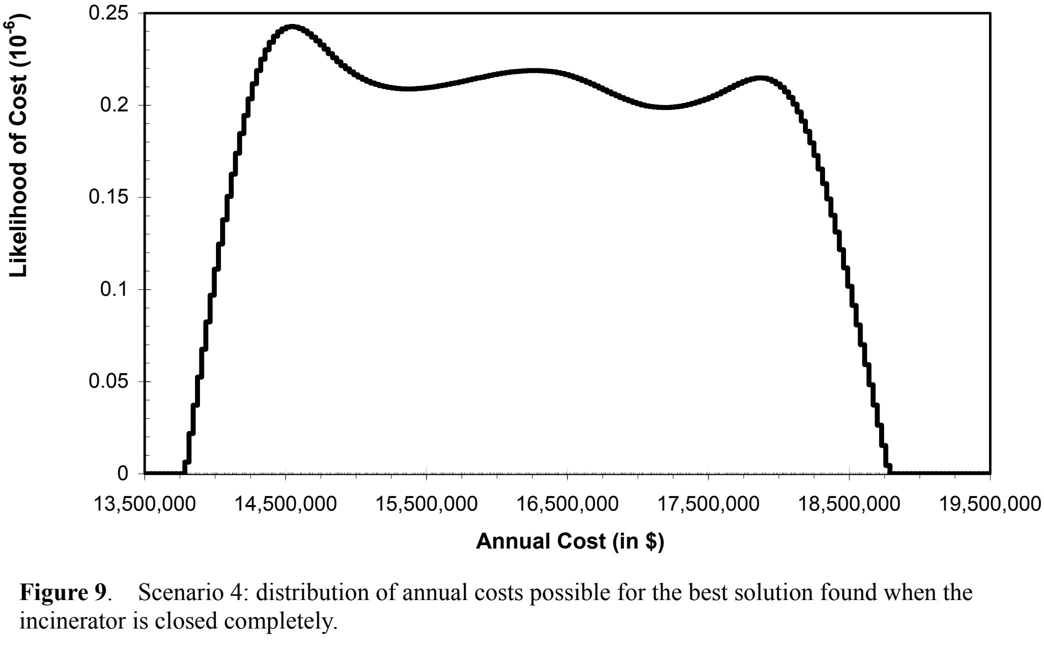

Figure 9. Scenario 4: distribution of annual costs possible for the best solution found when the incinerator is closed completely.

pality of Hamilton-Wentworth, they could also be readily extended and generalized to many such planning functions in any other municipality.

There were four scenarios considered in this research. When compared to the three scenarios previously examined in the earlier GLP study, GAS produced solutions that were superior in two cases and equivalent in the third. For the case in which the incinerator continued to operate at its current level, GAS demonstrated that costs could be reduced a further \$200,000 to 500,000 from the solution suggested by GLP; and this GLP solution had already shown that \$200,000 to 300,000 could be saved from the solution currently employed by the municipality. For the hypothetical scenario in which incinerator operations were increased to their maximum capacity levels, GAS produced a solution that was \$300,000 to 700,000 lower than the GLP solution. Only for the scenario in which the incinerator was completely shut down, did GAS not provide a better solution than GLP. An interesting scenario, not previously considered in the earlier GLP study, involved allowing the incinerator to operate at any level ranging between completely closing the facility up to operating it at its maximum possible capacity. In this case, it was shown that GAS could provide a solution that would save the municipality approximately \$1,300,000 from its current operations. This scenario was particularly interesting since it demonstrated that, overall, it was cheaper to continue to use the relatively more expensive SWARU incinerator (albeit at a lower level than its current operating capacity) than to close the facility completely.

Thus, it has been demonstrated that GAS and GLP can be easily and effectively combined to guarantee good results. It can be noted that evolutionary algorithm approaches, in general, possess a number of shortcomings. Namely, their solutions do not guarantee optimality, or even near-optimality, within a reasonable period of search time; the quality of the solutions found can depend upon the starting values used in their search process; and even searches commencing from identical starting points can produce very different solutions. Hence, it might be possible that a solely GA-based approach could take a significant period of time to produce a poor solution. In additional testing, Yoogalingam (2001) has demonstrated that this does not prove to be the case in the Hamilton-Wentworth application. However, earlier research has demonstrated that GLP, by itself, can be used to very quickly find a good, stable solution. This solution can then be used as the starting point for GAS analysis, in which GAS is employed to try to improve upon the original GLP solution. Therefore, the two-stage approach employed in this study overcomes all of the potential pitfalls found when using a strictly GA-based approach on its own (although GAS could readily be used exclusively to find solutions, with the usual In caveats applied when using any GA solution approach). Thus, the final solution determined will obviously never be any worse than the solution found by GLP. The time spent in the GAS improvement stage can be restricted to some fixed period of time; thereby placing an upper bound on the length of the search time. Hence, after some fixed period of time, at the very least, GAS will have produced the same solution as GLP. Furthermore, GAS provides stable solutions and may even be able to find stable solutions that had not been considered by the strictly GLP approach, as this study has demonstrated.

Other ancillary benefits have also arisen in conjunction with this research. The GLP procedure can be relatively easily implemented within a spreadsheet environment (together with some VBA programming) and can be solved using spreadsheet optimization add-ins. This finding, by itself, provides many practical advantages for the actual use of GLP by practitioners. By adopting such an interface, the GAS method can then also be implemented to run on the same spreadsheet model as GLP. Conversely, the GLP method could be run on the same spreadsheet model as GAS. Additionally, because GAS involves simulation in conjunction with genetic optimization, the method produces statistics and distributions of outcomes and outputs; not simply "single valued" objective function and decision variable values (although this is possible if no more information is desired). Hence, GAS readily permits average, percentile, and extreme value analysis simultaneously in a user-friendly, spreadsheet environment. Furthermore, if a spreadsheet is employed both for GAS models and GLP models, then this provides a simple interface to several, commercially available spreadsheet simulation packages. Given the solution settings on the spreadsheet (found either by GAS, GLP, or set by the user), simulation studies only (i.e. without considering any optimization component) can be run for any settings. This is extremely beneficial, since it permits complex sensitivity analysis and parametric programming to be performed (i.e. by simultaneously changing several parameters) as opposed to the single parameter changes permitted in the post-optimality analysis of optimization techniques. Hence, "what-if" options can be considered and evaluated very quickly starting from any spreadsheet settings and, as with GAS, statistics and distributions of outcomes can be produced.

A spreadsheet interface provides many practical advantages for method implementation by the actual users. Primarily, it is a natural analytical environment for many decision makers who are not, in general, trained OR professionals. This is beneficial, since it enables active end-user modelling, testing, and prototyping, which is absolutely essential if these methods and solutions are to ever be accepted and adopted. Spreadsheets provide an environment which are especially conducive to extremely rapid prototyping where solutions are needed quickly. Furthermore, "what-if" options and scenarios can be evaluated extremely rapidly using this spreadsheet interface. And most importantly of all, these solutions can all be generated internally by the municipal solid waste planners, saving a great deal of time and money by eliminating the reliance on outside technical consultants.

In summary, it is the practicality and "usability" of this approach which provides its biggest contribution. This study has demonstrated that good/useful solutions and alternatives can be found for the actual solid waste problem in the municipality of Hamilton-Wentworth. The study has demonstrated, for the first time, the practicality of employing evolutionary algorithms in conjunction with simulation for determining solutions to MSW management in which much of the data is uncertain. These solutions and this approach should prove invaluable for the planning and analysis in the newly proposed "Mega City".

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