ABSTRACT

KAPLAN, PERVIN OZGE. Consideration of Cost and Environmental Emissions of Solid Waste Management under Conditions of Uncertainty. (Under the direction of Dr. S. Ranjithan)

Among the many models and tools available for solid waste management (SWM), the integrated SWM decision support tool (ISWM DST) developed at North Carolina State University provides a comprehensive and integrated approach that considers cost and environmental factors associated with a large set of waste processing options. ISWM DST is designed to generate alternative SWM strategies that meet user-defined cost and environmental objectives. In addition to an array of site-specific inputs, this tool includes a large number of model parameters, which are currently treated deterministically with point estimates for inputs. A high degree of variability and uncertainty is known to exist in these input parameters, affecting the uncertainty in the model outputs. The absence of a systematic procedure to consider uncertainty in ISWM DST is a major drawback. The goal of this study is to develop and incorporate an uncertainty analysis component into ISWM DST. A Latin Hypercube Sampling (LHS) procedure is coupled with a simulation approach to enable uncertainty propagation. The capabilities of this new component are demonstrated using a realistic case study in which a series of scenarios are examined assuming uncertainty in a subset of the input parameters. For each scenario, the alternative strategy development capabilities of ISWM DST is first applied, the then each SWM strategy is evaluated under conditions of uncertainty. Performance of alternative

strategies is compared, and more reliable or robust strategies are identified. New and useful insights that were not apparent under deterministic conditions were gained, contributing more information to assist in SWM decision making. Further, correlation analysis was conducted to identify the uncertain input parameters that contribute mostly to the output uncertainty. This information is also expected to be valuable in making more informed decisions. In summary, this research contributes by significantly enhancing via the uncertainty analysis component the broad array of powerful capabilities of ISWM DST, making this tool more applicable in SWM planning and design practice.

Consideration of Cost and Environmental Emissions of Solid Waste Management under Conditions of Uncertainty

BY

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1. INTRODUCTION

With increasing need for considering an array of waste management issues (e.g., how much and what materials to recycle, should special yard waste collection and composting be implemented, how viable and beneficial is waste combustion in a community where disposal is constrained), and for improving the effectiveness of municipal solid waste management (SWM), the use of models and analysis tools is becoming more common. Several waste management tools were developed during the past three decades with a great variation in scope and methodology. These tools can be divided into two main categories. Some tools address analysis of single SWM unit operation, like collection [e.g., 5, 13], recyclable material recovery facilities (MRFs) [e.g., 14, 16], disposal operations [e.g., 8, 9, 12]. Others address analysis of integrated SWM systems that consider the interactions among a set of waste management operations. Most of these integrated SWM tools include a limited set of SWM unit operations and consider the cost of alternative SWM strategies [e.g., 1, 2, 11, 19, 20]. More recently, some integrated SWM tools incorporate environmental factors (e.g., emissions and energy consumption associated with waste management operations) in addition to cost [e.g., 4, 7, 10]. Lately, the environmental implications of SWM operations are being estimated more comprehensively and systematically via life cycle methodologies in a few SWM tools [e.g., 6, 17, 18, 23]. Of these tools, the computer based Integrated Solid Waste Management Decision Support Tool (ISWM DST) reported by Solano et al. [22, 23] and Harrison et al. [6] provides not only unit process level modeling capabilities that estimate cost , energy and emissions, but also a comprehensive approach for examining and

comparing integrated SWM strategies. ISWM DST is used in the analyses conducted in this study.

The underlying mathematical models in ISWM DST represent and integrate the mass flow and balance of waste items through a comprehensive set of unit processes for municipal waste management. This includes unit processes for collection, transfer, MRFs, treatment (including waste-to-energy facility, yard waste and mixed waste composting facilities), disposal of municipal solid waste (including traditional landfill and enhanced bioreactor landfill). When recyclable materials are recovered, the corresponding remanufacturing activities to process the recycled material are also modeled. For each feasible mass flow, this tool calculates the cost, energy consumption, and life cycle inventory (LCI) of emissions for a range of pollutants. A model for a unit process allocates the cost, energy, and LCI of the pollutants associated with handling a ton of a waste item in the municipal waste stream. Using these outputs from the unit process models, ISWM DST implements a linear programming-based search for integrated SWM strategies that meet user defined design goals. For example, one may identify for a given budget limit the most energy efficient SWM strategy that would yield 25% recycling for a municipality with a know generation rate and waste composition, as well as other site-specific conditions. This tool enables consideration of waste generated from different segments (e.g., single family residential, multi family residential, different commercial sectors) of the municipality.

Although ISWM DST is comprehensive and powerful, it currently treats all inputs and outputs as deterministic values, i.e., no uncertainty is explicitly considered within the underlying models and procedures. Like most other SWM tools, a large number of input values and site-specific information are needed to define an integrated SWM system. In addition, many process-specific constants (e.g., heat value of combustible waste items, density of loose and compact waste in collection trucks, fuel consumption and emission rates of vehicles and machinery used in waste processing) are used to estimate the cost, energy, and LCI emissions. Thus, the cost and environmental factors computed for an SWM strategy represent only point estimates, and do not reflect the associated uncertainties. This may be a drawback when using these estimates to compare alternative SWM strategies. For example, two strategies with similar point estimates for cost may have significantly different ranges when uncertainties are considered, thus making one strategy more robust or reliable than the other.

The primary goal of this research is to incorporate uncertainty analysis capabilities into ISWM DST, and demonstrate its application in a typical integrated SWM strategy development and decision making process. After implementing the uncertainty analysis procedures within ISWM DST, a procedure for using the new capabilities in comparing alternative SWM strategies is defined. Using this procedure, a decision maker could evaluate and consider the robustness of alternative SWM strategies under conditions of uncertainty. The proposed approach is demonstrated using a realistic case study. A series of typical SWM scenarios are defined and analyzed to illustrate how to apply the new capabilities of ISWM DST in SWM decision making.

2. PROBLEM DESCRIPTION

The approach taken in this research is described in the context of a hypothetical, but realistic, case study. Waste generation and management are being considered for a typical municipality of medium size. The essential characteristics of three segments of the community—single family homes, multi family homes, and commercial sector—are summarized in Table 1. The composition of waste generated by this community is listed in Table 2, and the waste management unit processes that are considered in this case study are listed in Table 3.

Table 1: Waste generation information for the community considered in the case study

	Population	Residents per house	Generation Rate, lb/person-day	Number of collection locations
Residential	450,000	2.63	2.64	N/A
MultiFamily	150,000	N/A	2.64	750
Commercial	N/A	N/A	3,700*	2,000

*lb/location-week

Table 2: Waste Stream Composition (by wet weight)

Waste Items	Residential Composition (%)	Multifamily Composition (%)	Commercial Composition (%)
Yard Trimmings, Leaves	0.056	0.056	N/A
Yard Trimmings, Grass	0.093	0.093	N/A
Yard Trimmings, Branches	0.037	0.037	N/A
Old News Print	0.067	0.067	0.022
Old Corr. Cardboard	0.021	0.021	0.360
Office Paper	0.013	0.013	0.072
Phone Books	0.002	0.002	0.003
Books	0.009	0.009	N/A
Old Magazines	0.017	0.017	N/A
3rd Class Mail	0.022	0.022	0.023
Paper Other #1	0.000	0.000	0.000
CCCR Other (1)	N/A	N/A	0.019
Mixed Paper	0.000	0.000	N/A
HDPE - Translucent	0.004	0.004	N/A
HDPE - Pigmented	0.005	0.005	N/A
PET	0.004	0.004	0.002
Plastic - Other #1	0.000	0.000	N/A
Mixed Plastic	0.000	0.000	N/A
CCNR Other (2)	N/A	N/A	0.041
Ferrous Cans	0.015	0.015	0.007
Ferrous Metal - Other	0.000	0.000	N/A
Aluminum Cans	0.009	0.009	0.004
Aluminum - Other #1	0.000	0.000	N/A
Aluminum - Other #2	0.000	0.000	N/A
Glass - Clear	0.039	0.039	0.019
Glass - Brown	0.016	0.016	0.008
Glass - Green	0.010	0.010	0.005
Mixed Glass	0.000	0.000	N/A
CNNR Other (3)	N/A	N/A	0.024
Paper - Non-recyclable	0.171	0.171	N/A
Food Waste	0.049	0.049	N/A
CCCN Other (4)	N/A	N/A	0.171
Plastic - Non-Recyclable	0.099	0.099	N/A
Misc. Combustible (5)	0.075	0.075	N/A
CCNN Other (6)	N/A	N/A	0.113
Ferrous - Non-recyclable	0.032	0.032	N/A
Al - Non-recyclable	0.005	0.005	N/A
Glass - Non-recyclable	0.007	0.007	N/A
Misc. (7)	0.123	0.123	N/A
CNNN Other (8)	N/A	N/A	0.107

(1) CCCR-Other represents commercial wastes that are combustible, compostable and recyclable.
(2) CCNR-Other represents commercial wastes that are combustible, non-compostable and recyclable.
(3) CNNR-Other represents commercial wastes that are non-combustible, non-compostable and recyclable.
(4) CCCN-Other represents commercial wastes that are combustible, compostable and non- recyclable.
(5) Miscellaneous-combustible represents wastes from the residential and multifamily sectors that are combustible but non-recyclable.
(6) CCNN-Other represents commercial wastes that are combustible, non-compostable and non-recyclable.
(7) Miscellaneous represents wastes from the residential and multifamily sectors that are non-combustible and non-recyclable.
(8) CNNN-Other represents commercial wastes that are non-combustible, non-compostable and non-recyclable.

Table 3: Waste management unit processes included in the case study

Residential Collection	Collection of yard trimmings for aerobic composting
	Collection of mixed MSW in one truck prior to separation of any component
	Collection of commingled recyclables (sorted at the point of collection by the collection crew)
	Collection of pre-sorted recyclables
	Collection of commingled recyclables (to be sorted at a MRF); ONP in separate compartment
	Collection of mixed MSW after removal of recyclables or yard waste
	Recyclables drop-off by the generator
Multifamily Collection	Recyclables drop-off by the generator
	Collection of mixed MSW
	Collection of pre-sorted recyclables (multiple bins)
	Collection of commingled recyclables (two bins, ONP separate)
	Collection of MSW after removal of recyclables via C14 or C15
Commercial Collection	Collection of pre-sorted recyclables
	Collection of mixed MSW
	Collection of Residuals
Separation	Sorting of mixed refuse
	Processing of pre-sorted recyclables collected via C2 and C3
	Sorting of commingled recyclables collected via C4
Treatment	Aerobic composting of yard waste
	Combustion with electric power generation
Disposal	Landfill
	Ash Landfill

The overall focus of this case study is to identify and compare alternative SWM strategies (i.e., which unit processes should be included, and the associated waste flow through these unit processes) that meet cost and environmental emissions goals. Greenhouse gas emissions (expressed as carbon equivalents, and indicated by GHE) and NO_x emissions are the two environmental factors that are considered. The study must also incorporate targets for waste diversion from the landfill disposal. The comparisons must be conducted not only under deterministic conditions, but also when some key input parameters are assumed to be uncertain.

While a large number of the model inputs can be assumed to be known with sufficient certainty, several parameters are identified as uncertain. In this case study, the input parameters listed in Table 4 are considered as uncertain. These parameters are assumed to be non-correlated, which allows the probability distributions of each parameter to be independent of each other. To determine the appropriate probability distributions of these uncertain parameters, historical data and limited expert judgment was used. Statistical properties to define the associated probability distribution were estimated accordingly. Although formal methods [15] for quantifying expert opinion exist, they are not implemented in this study.

Table 4: Uncertain input parameters

COLLECTION	Units	Type of Distribution	Range	Most Likely Value
number of households at one service stop	hh/stop	triangular dist	1, 2	1
loading time at one service stop	min/stop	triangular dist	3, 12	5
travel time between route and disposal facility	min/trip	triangular dist	10, 50	20
fuel usage rate while travelling	miles/gallon	triangular dist	5, 9	5
MRF				
Baler's electricity usage	kwh/ton	triangle dist	10, 14	12
COMBUSTION				
Heat rate	BTU/kWh	triangular dist	16000, 20000	18000
LANDFILL				
height of waste above grade	ft	triangular dist	40, 200	40
excavation depth	ft	triangular dist	20, 50	40
compacted waste density	lb/yd3	triangular dist	1200, 1800	1500
Landfill Total Gas Yield Data Source (SWANA data vs Lab Data)	-	triangular dist	0 - 1	
Percent by volume that is not collected by landfill gas collection system	%	triangular dist	10, 40	12
K, Decay rate	1/years	triangular dist	0.02, 0.08	0.03
Landfill Total Gas Yield (based on SWANA data)	ft3 gas/ton MSW	triangular dist	3200, 7200	5165
Percent oxidation to CO2 of uncollected methane gas	%	triangular dist	10, 50	15

3. METHODOLOGY

The ISWM DST was used to model and analyze this case study. Its existing capabilities were used to represent the problem. The waste generation and composition information were appropriately input to the model. The default input data and information for the unit processes were assumed to be the same as those used in the study reported by Solano et al. [22]. Using the ISWM DST, first the SWM strategies were identified under deterministic conditions. For each strategy, the set of unit processes and the corresponding mass flow of each waste item through these unit processes were identified. The resulting deterministic estimates of cost, GHE, and NO_x emissions were also computed.

To explore alternative strategies, the modeling to generate alternatives (MGA) capabilities embedded within ISWM DST was utilized. MGA methods generate near optimal solutions that have maximally different values for the decision variables. Hop, Skip and Jump (HSJ) [3] is an MGA method applicable to a range of mathematical models. This procedure involves an iterative process of optimizing reformulated versions of the original optimization model. To find an alternative, the original objective function is replaced with the objective of minimizing the decision variables that were non-zero in the previous solutions while ensuring the original objective function value to be within a specified relaxation over the optimal value. This new objective function forces the model to select decision variable values such that the variables that were selected in the previous solutions are avoided as much as possible.

The MGA utilities in ISWM DST were applied to generate alternative SWM strategies. The resultant alternative SWM strategies with distinctly different sets of unit processes and waste flows represent different characteristics. Thus, these alternatives are expected to perform differently with respect to different criteria, including reliability or robustness under conditions of uncertainty. Therefore, generation of alternatives using MGA is likely to improve the chances of finding strategies that are more robust under uncertainty.

While the deterministic estimates of cost and environmental emissions can be useful in comparing alternative strategies, output variability under conditions of uncertainty are critical in identifying the most robust or reliable strategy. Sources of uncertainty can be listed as statistical variation, subjective judgment, linguistic imprecision, variability, inherent randomness, disagreement, or approximation [15]. The resulting uncertainty in cost, GHE, and NO_x emissions for each strategy needs to be estimated. This is accomplished via a systematic procedure for uncertainty analysis that is coupled with ISWM DST.

Several techniques can be applied to study parameter uncertainty in models. Morgan and Henrion [15] categorize these methods into sensitivity analysis, uncertainty propagation, and uncertainty analysis. Most common and simple way is to use sensitivity analysis, which shows the rate of change of model outputs with respect to variation in a particular input. Instead, uncertainty propagation can be used to calculate the uncertainty in model outputs caused by uncertainty in model inputs. Also uncertainty analysis can be

conducted to compare the importance of uncertain input parameters with respect to their contributions to output uncertainty.

One of the commonly known approaches for simulating uncertainty is to use Monte Carlo sampling methods, in which a value is drawn at random from the distribution for each input parameter. A set of values for all uncertain parameters forms an input scenario or realization. For each input realization, the model outputs are estimated. By repeating this process N times, N independent samples of each output can be obtained. These N output values constitute random samples from the probability distribution over the inputs. This data can be used for generation of cumulative distribution functions (CDFs) of the outputs. For a given output distribution, the accuracy of the estimates depends on the size of the sample, N, but not on the number of uncertain input parameters.

By recognizing the importance of uniformly distributed, stratified samples of points in the sample space are recognized, more appealing systematic and stratified sampling methods can be employed. Latin Hypercube Sampling (LHS) technique is an example of stratified sampling methods. In stratified sampling, the sample space, generally the Probability Density Function (PDF), is divided into strata, and input values are obtained by sampling separately from within each stratum instead of from the whole probability distribution. For example, to obtain N samples using LHS, each input parameter distribution is divided into N equiprobable intervals.

In this study, Monte Carlo simulation with 200 realizations was carried out to estimate the output uncertainty for each SWM strategy. For each realization, the unit cost and emission rates (per unit mass of waste item treated in a unit process) were computed. These are then combined with the mass flows of waste items corresponding to an SWM strategy to estimate the total cost and environmental emissions. After repeating this for all realizations, the resultant cost and emission values were compiled to estimate their cumulative distribution functions, as well as to compute the correlation coefficients between each uncertain input and an output parameter. These results can be used with the aid of standard statistical techniques to obtain the confidence interval about the mean of an output CDF or other point estimates of interest (e.g., the deterministic estimate). Also, correlation analyses can be conducted to determine the relative importance of uncertain input parameters on the model predictions.

4. ANALYSES AND RESULTS

The overall purpose of the analyses conducted in this research is to demonstrate the applicability of the proposed approach in evaluating and comparing the performances of alternative SWM strategies under conditions of uncertainty. First, the ISWM DST was applied to the community described in the previous section to generate the best SWM strategies under deterministic conditions for the following scenarios: 1) least cost alternatives to meet a target diversion rate; and 2) alternative strategies to minimize carbon equivalence of greenhouse gas emissions (GHE) within a target cost restriction. In all scenarios, cost, GHE, and NO_x emissions were computed. All strategies were then subjected to uncertainty in the input parameters identified in Table 4, and the corresponding probability distributions of the uncertainty in cost and environmental emission estimates was computed. Robustness and the differences among the strategies were compared. Correlation coefficients were computed to identify the relative contributions of the uncertain parameters to the output uncertainty. These scenarios and the results are described in the following subsections.

4.1 Base Case: Least-Cost Strategy

The ISWM DST was used to identify the least-cost SWM strategy that meets a 25%-diversion requirement. The 25% diversion constitutes by mass waste recovered as recyclable material and yard waste that was not sent to a landfill. This strategy was generated assuming deterministic estimates for all model input parameters. The resulting choices of waste processing options, the waste flow through them, and the deterministic estimates of cost and emissions are summarized in Table 5.

The parameters listed in Table 4 were then treated as uncertain, and the LHS sampling procedure was applied to generate 200 random realizations. For each realization, the cost and emissions estimates associated with the least-cost strategy were then computed. These estimates for each output parameter (i.e., cost, GHE, and NO_x emissions) were then compiled to represent the probability distributions. The resulting CDFs are shown in Figures 1-3. The deterministic estimates of each output parameter are also indicated in these figures.

Figure 1, which shows the CDF of the total annual cost, indicates that the total annual cost vary between $27.6 million and $37.0 million under conditions of uncertainty. Although the expected cost of the least-cost strategy is $32.1 million, there is a 32.5% likelihood of exceeding deterministic cost estimate of $32.9 million.

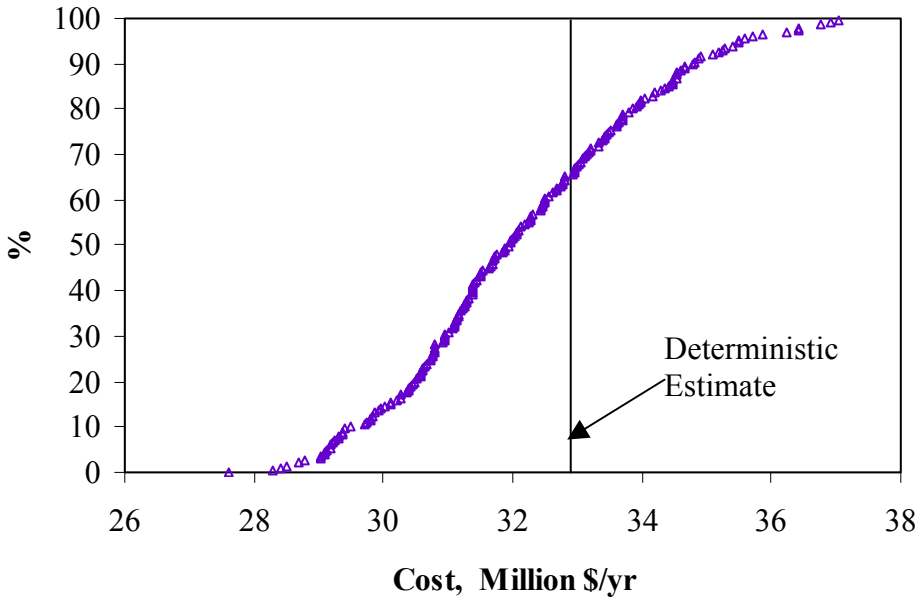

Figure 1: CDF for the annual cost of the least-cost SWM strategy under conditions of uncertainty

Table 5: Least Cost SWM Strategies: comparison of mass flows, cost, and emissions

Mass Flows, tons/year	Least Cost (LC Alt 0)	Alternative 1 (LC Alt 1)	Alternative 2 (LC Alt 2)	Alternative 3 (LC Alt 3)
R-Yardwaste	0	14,400	2,370	18,100
R-Mixed Waste	0	44,500	189,000	0
R-Residuals	205,000	149,000	24,400	187,000
R-Recyclable Drop-Off	11,500	9,110	1,530	11,700
MF-Recyclable Drop-Off	0	0	3,910	0
MF-Mixed Waste	0	72,300	0	0
MF-Pre-Sorted	7,580	0	0	0
MF-Commingled	0	0	0	7,940
MF-Residuals	64,700	0	68,400	64,300
C-Pre-Sorted	50,800	44,600	50,800	50,800
C-Mixed Waste	0	23,400	0	0
C-Residuals	142,000	124,000	14,200	142,000
Mixed Waste	400,000	341,000	423,000	188,000
Presorted	69,900	53,800	56,300	62,500
Commingled	0	0	0	7,940
Yardwaste Compost	0	14,400	2,370	18,100
Combustion	0	0	43,000	7,750
Landfill	361,000	36,100	318,000	353,000
Ash-landfill	0	0	10,700	2,090
Cost/LCI values				
Green House Equivalents, tons/year	9,760	12,500	1,440	12,700
Nitrogen oxides, tons/year	-544,000	-445,000	-766,000	-420,000
Cost, $/year	32.9 Million	38 Million	38 Million	38 Million

Similarly, one can conclude from Figure 2 that GHE for the least-cost strategy under uncertainty varies between 4.1 thousand tons/year and 23.1 thousand tons/year. While the expected GHE is 13.3 thousand tons/year, there is an 80% likelihood of exceeding the deterministic estimate of 9.76 thousand tons/year. NO_x estimates under uncertainty shown in Figure 3 indicate that NO_x emissions vary between -527.7 thousands tons/year and -524.7 thousand tons/year. The likelihood of exceeding the deterministic estimate of –547 thousand tons/year is about 38%.

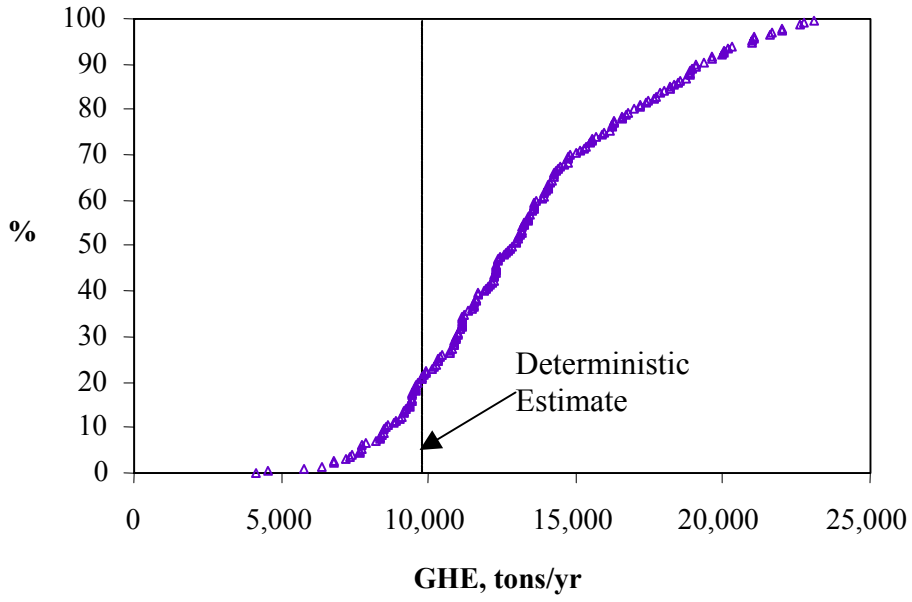

Figure 2: CDF for the annual GHE corresponding to the least-cost SWM strategy under conditions of uncertainty

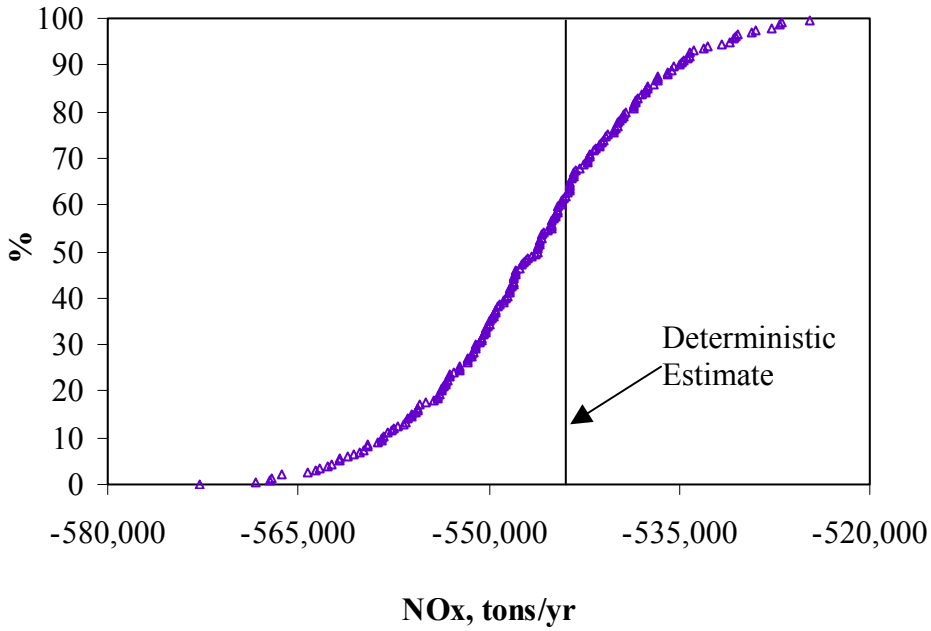

Figure 3: CDF for the annual NO_x emissions corresponding to the least-cost SWM strategy under conditions of uncertainty

4.2 Alternative Least-Cost SWM Strategies

The ISWM DST was applied once again to generate three additional least-cost SWM alternatives. The MGA capabilities available within ISWM DST were utilized to identify three different SWM strategies that cost no more than $38 million/year (about 15% more than the least cost). These alternatives were generated such that different waste processing options and waste flows were selected as much as possible in these alternative strategies. The mass flows, costs, and emissions estimates for these alternatives are summarized in Table 5.

As in the least-cost scenario, the performances of these alternatives were estimated under conditions of uncertainty. The resulting CDFs are shown in Figures 4-6. Graphs in these

figures can be used to estimate the likelihood of exceeding the deterministic estimates for cost, GHE, and NO_x emissions. For example, the likelihood of exceeding the deterministic estimates for cost are approximately 40%, 32%, and 58% for Alternatives 1, 2, and 3, respectively. In terms of environmental performance, Alternative 2 clearly dominates the other alternatives (Figures 5 and 6).

Summary statistics for these alternatives are listed in Table 6. It can be observed that expected costs of all SWM alternatives except Alternative 3 are less than those of the corresponding deterministic values. In terms of environmental performance, expected GHE values are higher than those of the corresponding deterministic values in all cases, while the expected NOx values are less than the corresponding deterministic NOx estimates for Alternatives 0 and 2.

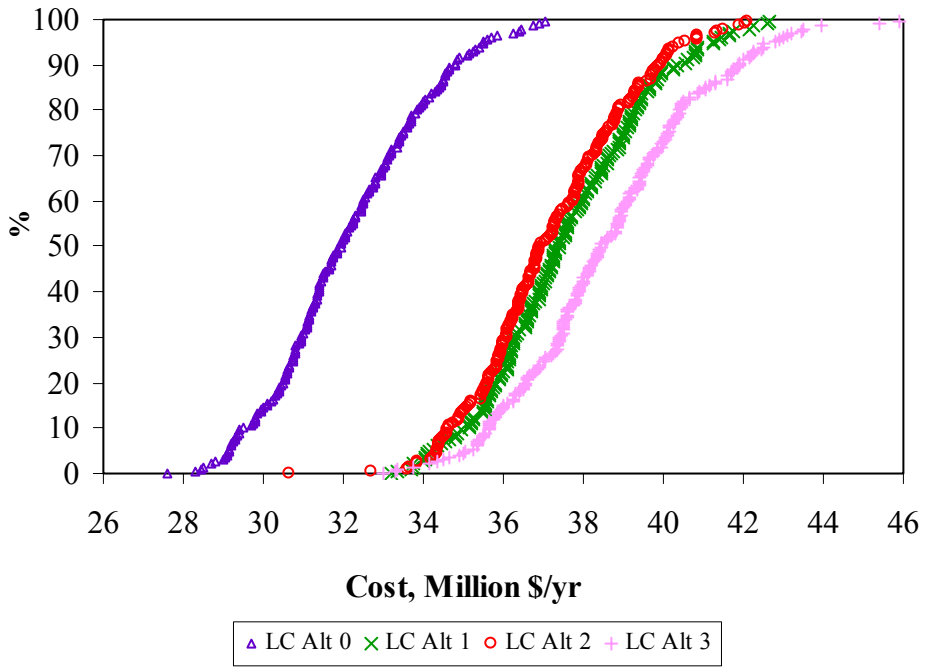

Figure 4: CDFs for the annual cost of the alternative least-cost SWM strategies under conditions of uncertainty

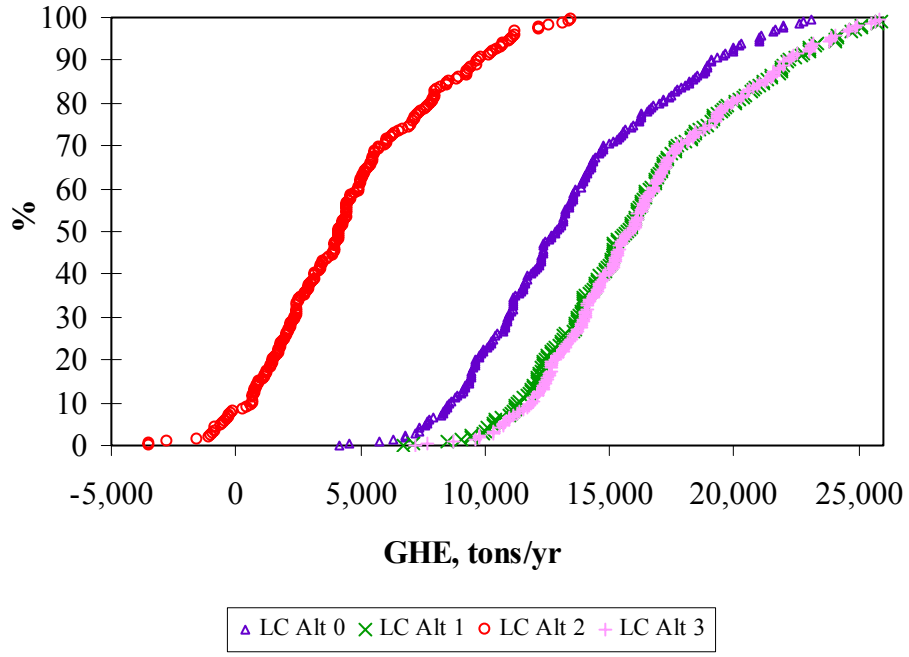

Figure 5: CDFs for annual GHE of the alternative least-cost SWM strategies under conditions of uncertainty

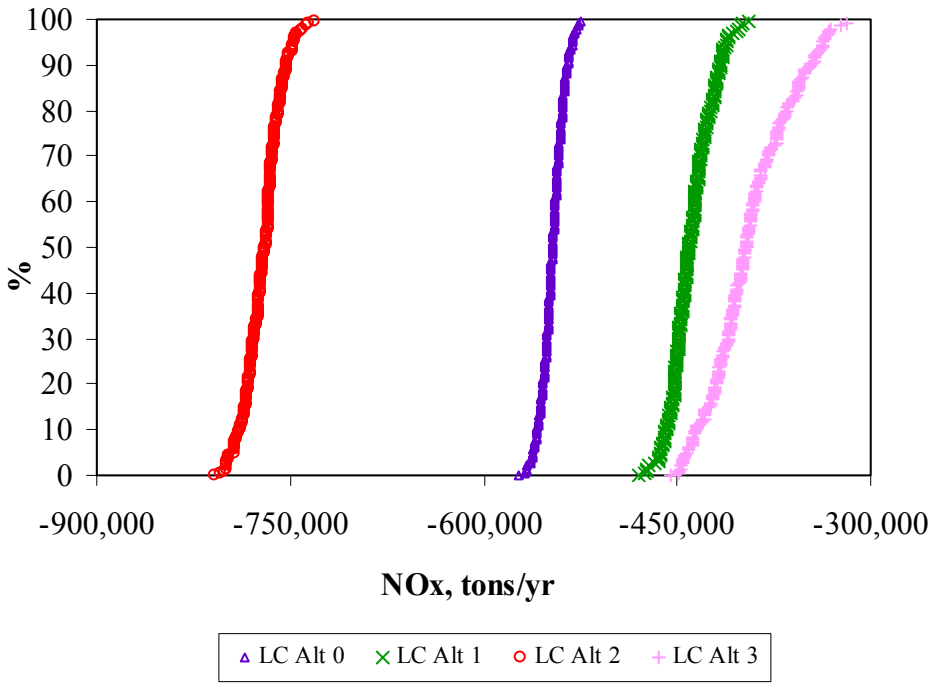

Figure 6: CDFs for annual NO_x emissions of the alternative least-cost SWM strategies under conditions of uncertainty

Table 6: Least cost SWM alternatives: cost, GHE, and NO_x comparisons under conditions of uncertainty

	Least Cost (LC Alt 0)	**Alternative 1 (LC Alt 1)**	**Alternative 2 (LC Alt 2)**	**Alternative 3 (LC Alt 3)**
Cost, $/yr				
Deterministic Estimate	32,900,000	38,000,000	38,000,000	38,000,000
Expected Value	32,100,000	37,500,000	37,200,000	38,600,000
Standard Deviation	1,960,000	2,030,000	1,970,000	2,360,000
GHE, tons/yr				
Deterministic Estimate	9,760	12,500	1,440	12,700
Expected Value	13,300	16,200	4,530	16,300
Standard Deviation	4,000	4,120	3,530	3,940
Nox, tons/yr				
Deterministic Estimate	-544,000	-445,000	-766,000	-420,000
Expected Value	-547,000	-439,000	-771,000	-394,000
Standard Deviation	8,960	16,100	14,200	31,400

4.3 Performance Differences between Alternatives

Although the information presented above provide a means for comparing these alternatives, the difference between any two alternatives needs to be further characterized statistically. The above comparisons do not consider the difference in performance between two alternatives with respect to each realization. The CDF of the differences corresponding to each realization needs to be estimated. This is obtained for a pair of alternatives by first computing the difference in an output parameter (e.g., cost, GHE, or NO_x emissions) for each realization, and then the CDF of the differences is generated. Figures 7-9 show these CDFs corresponding to each alternative (LC Alt 1, LC Alt 2 and LC Alt 3) and the least-cost strategy (LCAlt 0).

These CDFs of the differences provide insights that were not apparent from the comparisons described in Section 4.2. For example, Alternative 2 costs about $5 million/yr over the least cost (i.e., $38 million/yr vs. $32.9 million/yr) with low variability (Figure 7), while consistently performing better with respect to GHE and NO_x emissions (Figures 8 and 9). Also, it is evident from these figures that Alternatives 1 and 3 have a higher degree of variability in cost with high degree of exceedence over the $5 million/yr cost difference. Further, these alternatives result in increased emissions 100% of the time. Thus, if one were to spend an additional $5 million/yr towards reducing the emissions, Alternative 2 appears to be a more robust strategy compared to Alternatives 1 and 3.

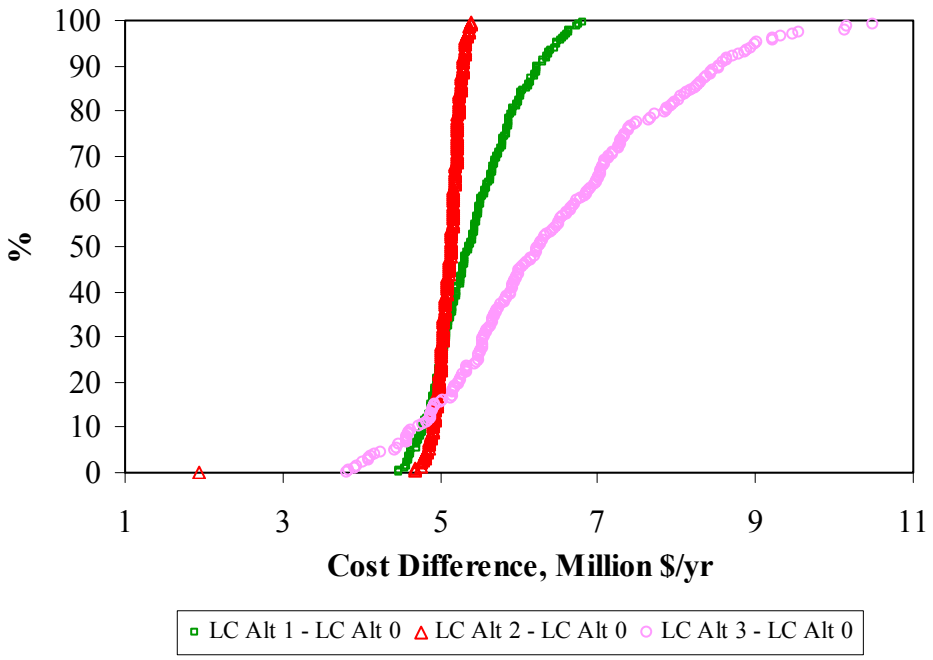

Figure 7: CDFs of the differences in cost of an alternative and the least-cost strategy

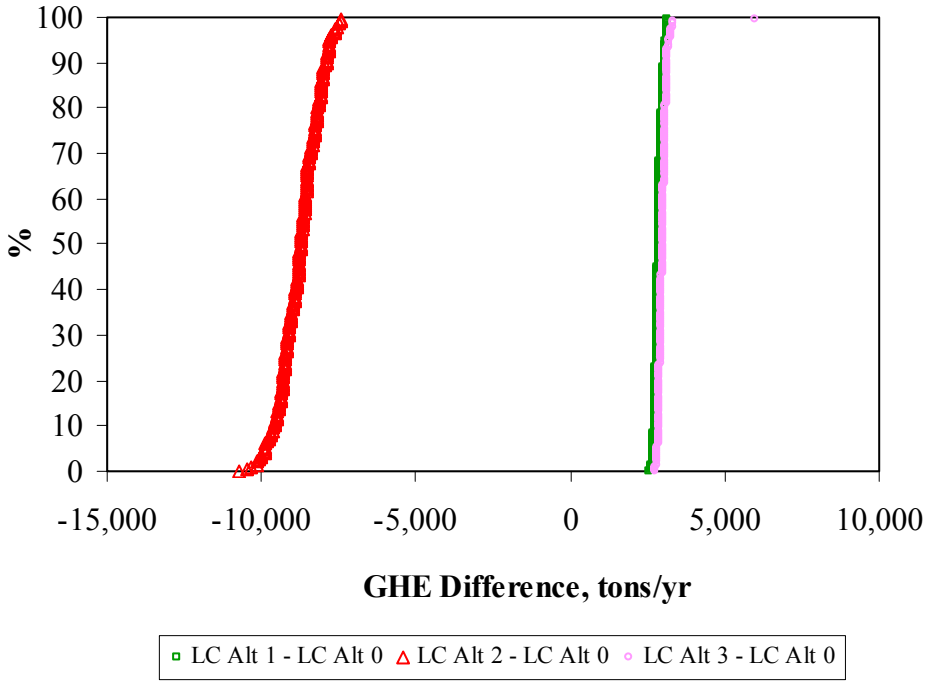

Figure 8: CDFs of the differences in GHE of an alternative and the least-cost strategy

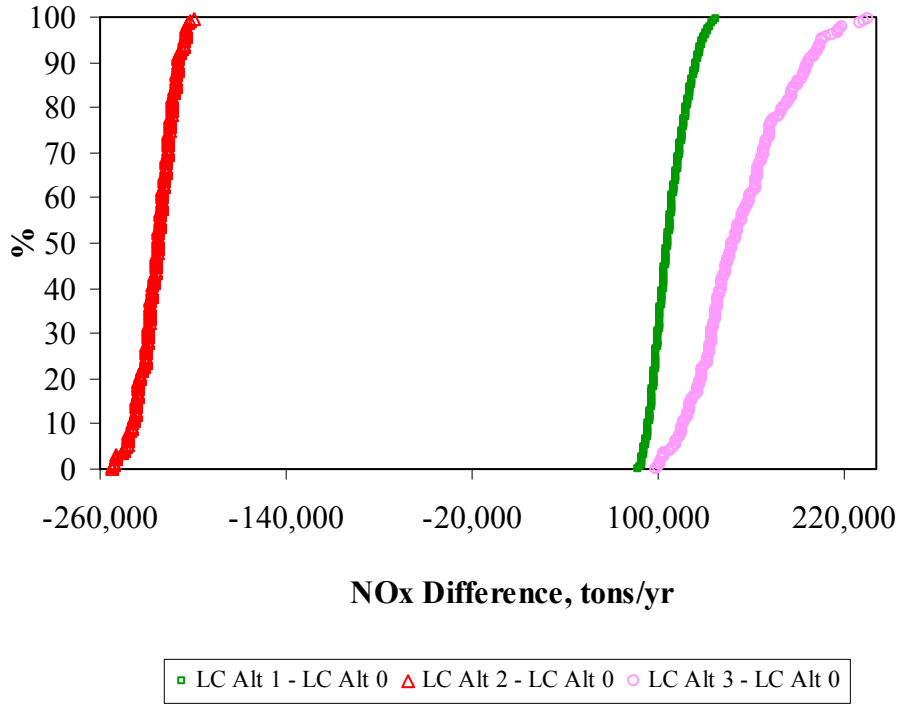

Figure 9: CDFs of the differences in NO_x of an alternative and the least-cost strategy

4.4 Correlation Analysis

Further analysis is conducted to estimate the correlation between the uncertain input and output parameters. The correlation gives an estimate of the linear contribution of each uncertain input parameter to the output uncertainty. The goal is to identify the relative impact of each uncertain parameter on the output uncertainty. This is achieved by estimating the correlation coefficients, which are inherently global measures of uncertainty importance obtained by averaging the effect of one input parameter over the joint probability distribution function for all other input parameters. Magnitude of the correlation coefficient is used to indicate how much the uncertainty of a parameter affects model predictions.

Table 7 tabulates a subset of strongly and weakly correlated uncertain parameters to cost and GHE. For example, number of households per stop during the residential mixed waste collection operation is the most (negatively) correlated parameter for cost. This mean that variation in the number of households per stop affects the overall cost of the strategy more than other uncertain input parameters considered in this study. Also, the negative sign indicates that as the number of households per stop increases, the cost will decrease, which can be intuitively verified. Another example is the percent of landfill gas not collected by gas collection system that is most (positively) correlated with GHE. This means that GHE is affected mostly by the variation of gas collection efficiency among the uncertain parameters considered in this study. Also, GHE decreases as the collection efficiency decreases (or the fraction not collected increases). Information obtained from such a correlation study can be valuable in evaluating the benefits of improving the estimates of uncertain input parameters to attain model predictions with higher degree of certainty.

Table 7: Subset of uncertain parameters that are strongly/weakly correlated to cost and GHE

COST, $/year	Correlation Factor
Number of Households per stop, (C1, Residential Mixed Waste Collection)	-0.6481
Landfill Total Gas Yield Data Source (SWANA data vs. LAB DATA)	-0.0005
Loading time at one service stop, min/trip, (C1, Residential Mixed Waste Collection)	0.6262
GHE, tons/year	
% oxidation to CO2 of uncollected methane gas	-0.3572
Height of waste above grade, ft, (Landfill)	0.0015
Percent by volume that is not collected by landfill gas collection system, landfill	0.6992

4.5 Alternative Least GHE Emissions Strategies

Similar to the least-cost strategies described above, a set of strategies that minimize GHE while meeting a $50 million/yr cost limit were generated. No explicit diversion target was imposed in these cases. Again, the ISWM DST was applied first to find the least GHE strategy under deterministic conditions. This solution is summarized in Table 8. The lowest GHE that can be achieved is –43.2 thousand tons/year (LGHE Alt 0 in Table 8). The alternatives utilizing maximally different unit operations were generated with a 25% relaxation on GHE, i.e., not to exceed a GHE value of –32.4 thousand tons/year. The resulting alternative strategies are also listed in Table 8.

These alternative strategies were then evaluated under conditions of uncertainty for 200 random realizations generated through LHS sampling for the uncertain parameters in Table 4. The resulting CDFs of cost, GHE, and NO_x emissions for the least GHE alternative (LGHE Alt 0) are shown in Figures 10-12. Summary statistics are listed in Table 9.

As in the previous cases, the likelihood of meeting the target cost and emissions values can be estimated from these CDFs. For example, while the expected cost of LGHE Alt 0 is $50.5 million/yr, there is about 60% likelihood of exceeding the target $50 million/yr cost limit (Figure 10). Cost for this strategy may vary between $46.5 and $58.4 million/yr, indicating a wide range of potential variation in cost under conditions of uncertainty. Similarly, the GHE under uncertainty exceeds the deterministic estimate of –42.8 thousand tons/year approximately 55% of the time, with a range from -50.4

thousand tons/year to -36.3 thousand tons/year (Figure 11). NO_x emissions vary between -1.42 million tons/year and -1.04 million tons/year with about 55% likelihood of exceeding the deterministic estimate of –1,220 thousand tons/year (Figure 12).

Table 8: Least-GHE SWM Strategies: comparison of mass flows, cost, and emissions

Mass Flows, tons/year	**Least GHE (LGHE Alt 0)**	**Alternative 1 (LGHE Alt 1)**	**Alternative 2 (LGHE Alt 2)**	**Alternative 3 (LGHE Alt 3)**
R-Mixed Waste	0	217,000	0	0
R-Residuals	207,000	0	206,000	207,000
R-Recyclable Drop-Off	10,200	0	10,400	10,200
MF-Recyclable Drop-Off	0	0	3,390	0
MF-Mixed Waste	0	72,300	0	0
MF-Pre-Sorted	7,540	0	0	0
MF-Commingled	0	0	0	5,420
MF-Residuals	64,700	0	68,900	66,900
C-Pre-Sorted	36,800	0	50,800	41,500
C-Mixed Waste	0	192,000	0	0
C-Residuals	156,000	0	142,000	151,000
Mixed Waste	0	250,000	0	0
Presorted	54,600	0	64,600	51,700
Commingled	0	0	0	5,420
Combustion	362,000	231,000	387,000	357,000
Landfill	64,700	219,000	29,500	66,900
Ash-landfill	91,900	52,900	101,000	91,400
Cost/LCI values				
Green House Equivalents, tons/year	-43,200	-33,400	-42,700	-41,700
Nitrogen oxides, tons/year	-1,220,000	-708,000	-1,410,000	-1,260,000
Cost, $/year	50 Million	50 Million	50 Million	50 Million

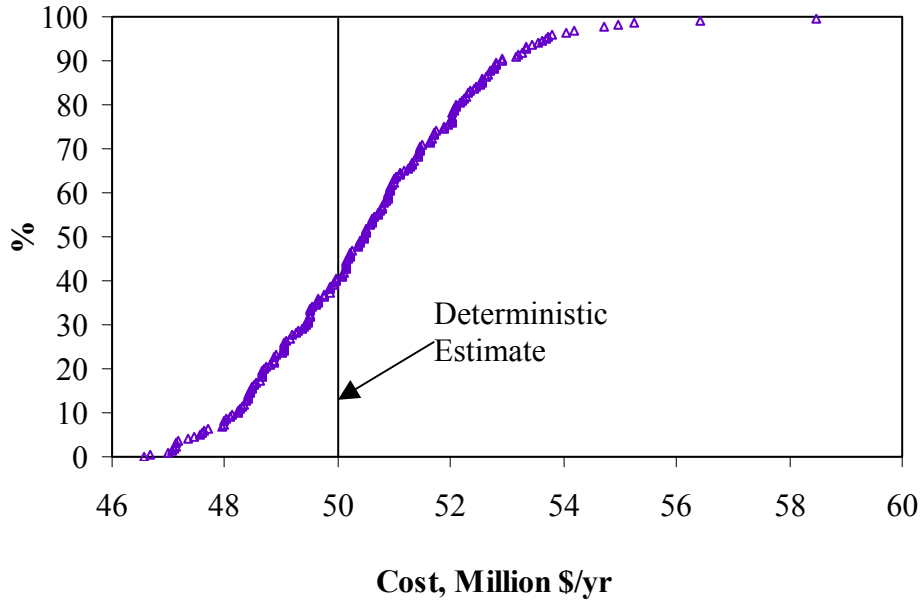

Figure 10: CDF for the annual cost of the least-GHE SWM strategy under conditions of uncertainty

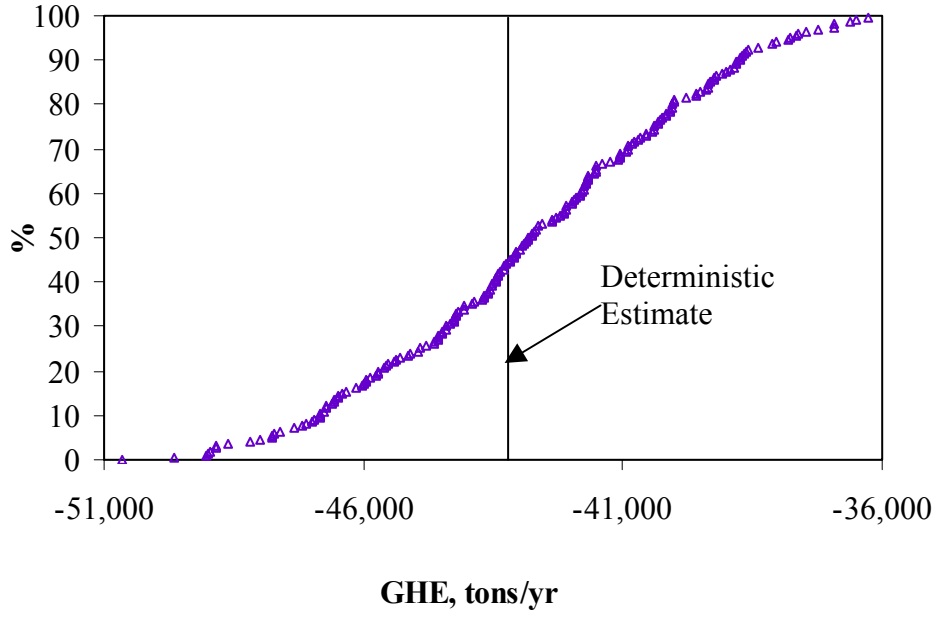

Figure 11: CDF for the annual GHE corresponding to the least-GHE SWM strategy under conditions of uncertainty

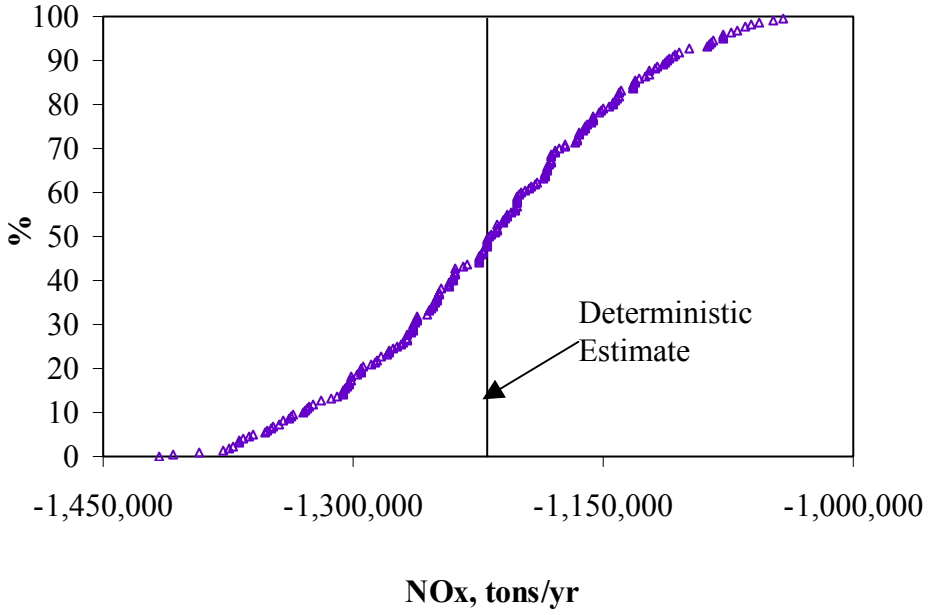

Figure 12: CDF for the annual NO_x emissions corresponding to the least-GHE SWM strategy under conditions of uncertainty

CDFs of all the alternatives are compared in Figures 13-15. Like the least-GHE strategy, the alternatives also exceed their respective deterministic cost estimates, with likelihood ranging from about 34% to 60% (Figure 13). When comparing the emissions under conditions of uncertainty (Figures 14-15), there is a high degree of likelihood (ranging from 55%-75% for GHE, and 45%-55% for NO_x emissions) of exceeding the corresponding deterministic estimates.

Table 9: Least-GHE SWM Alternatives: cost, GHE, and NO_x comparisons under conditions of uncertainty

	Least GHE (LGHE Alt 0)	**Alternative 1 (LGHE Alt 1)**	**Alternative 2 (LGHE Alt 2)**	**Alternative 3 (LGHE Alt 3)**
Cost, $/yr				
Deterministic Estimate	50,000,000	50,000,000	50,000,000	50,000,000
Expected Value	50,500,000	49,300,000	50,400,000	50,500,000
Standard Deviation	1,950,000	1,890,000	1,860,000	1,880,000
GHE, tons/yr				
Deterministic Estimate	-43,200	-33,400	-42,700	-41,700
Expected Value	-42,800	-31,500	-42,600	-41,300
Standard Deviation	3,080	3,050	3,180	3,010
Nox, tons/yr				
Deterministic Estimate	-1,220,000	-708,000	-1,410,000	-1,260,000
Expected Value	-1,220,000	-715,000	-1,410,000	-1,250,000
Standard Deviation	81,600	57,000	84,500	79,600

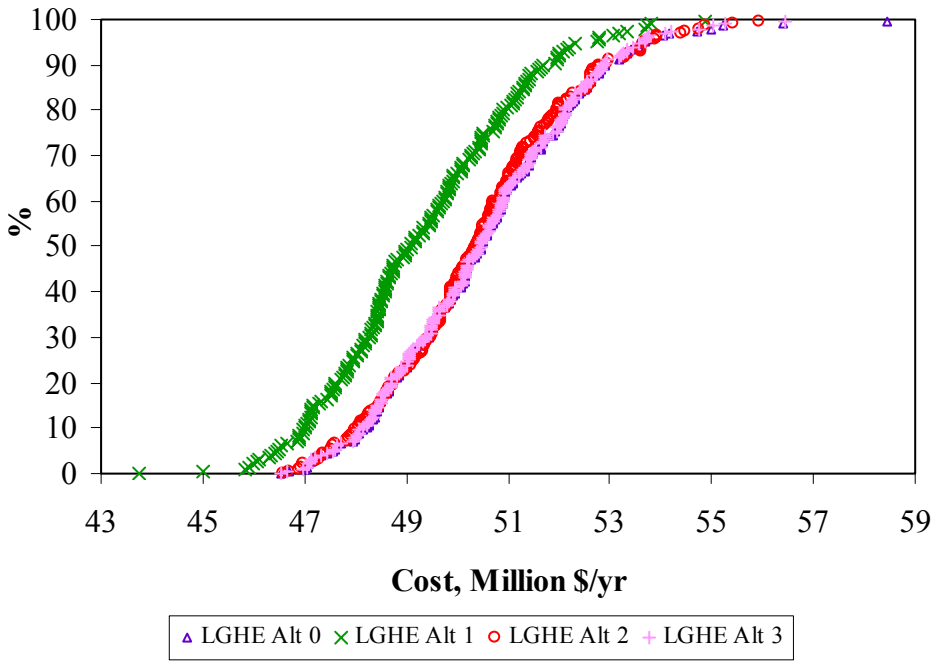

Figure 13: CDFs for the annual cost of the alternative least-GHE SWM strategies under conditions of uncertainty

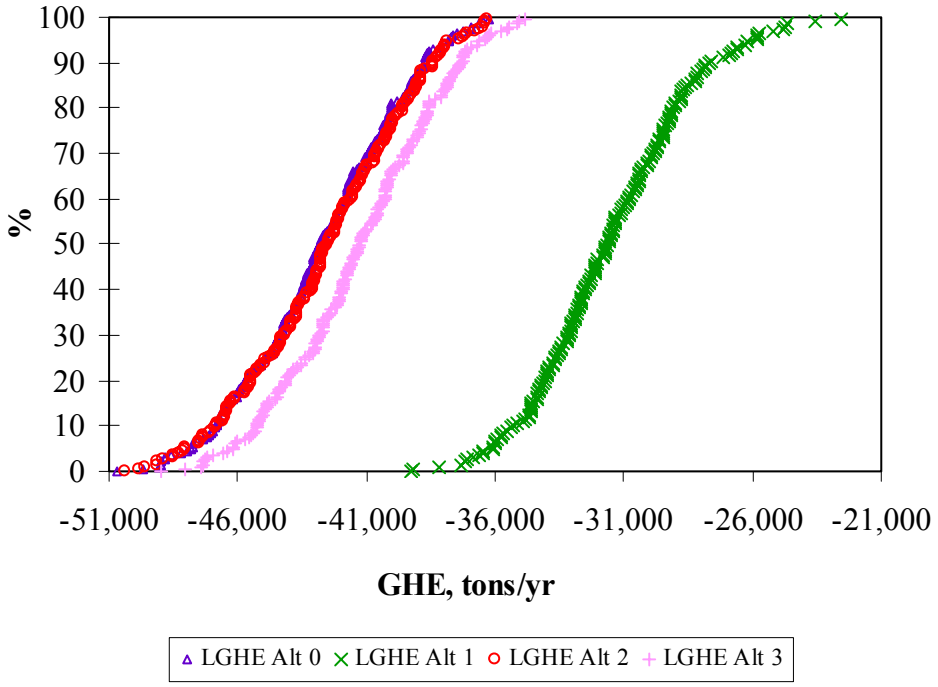

Figure 14: CDFs for annual GHE of the alternative least-GHE SWM strategies under conditions of uncertainty

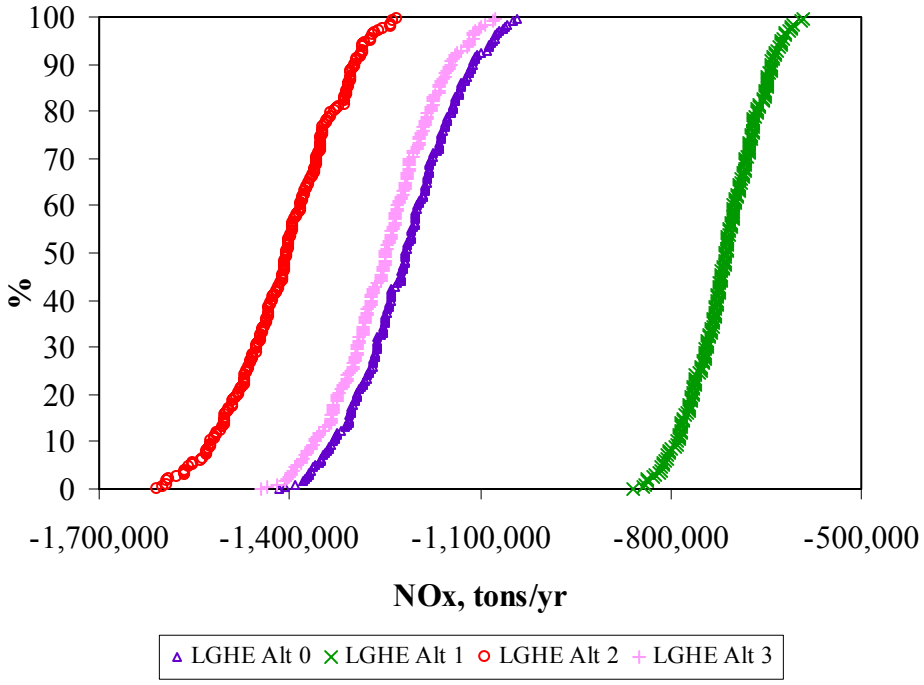

Figure 15: CDFs for annual NO_x emissions of the alternative least-GHE SWM strategies under conditions of uncertainty

5. SUMMARY AND CONCLUSION

An LHS-based uncertainty propagation procedure was implemented and integrated with ISWM DST. This enables the specification of the input parameters to ISWM DST as uncertain with user-defined probability distributions. Coupling the uncertainty propagation procedure with the existing capabilities of ISWM DST to generate alternative SWM strategies that meet cost and environmental goals, a user is now able to evaluate and compare the performance of SWM strategies under conditions of uncertainty. In addition, the new implementation includes a procedure to compute the correlation coefficients that could help identify the uncertain parameters that mostly contribute to the uncertainty in the model outputs.

Applications of the new procedures were demonstrated using an illustrative case study for a hypothetical municipality. SWM scenarios considering cost and environmental objectives were analyzed. Greenhouse gas and NO_x emissions were used to represent the environmental objectives. The ISWM DST was used to generate alternative SWM strategies under deterministic conditions. The uncertainties in cost and environmental emissions for these strategies were then evaluated when a set of input parameters are known to be uncertain.

Results from these illustrative scenarios yield several interesting observations. Although the alternative SWM strategies performed similarly with respect to the deterministic estimates for cost and environmental emissions, their performance under uncertainty

were distinctly different. Additional analysis was conducted to examine the difference in performance between pairs of strategies. This provided further insights that were not apparent otherwise. For example, when comparing three alternatives with another, one strategy was found to be clearly superior (both in the context of variability and the amount of improvement in environmental performance), which was not revealed from other analyses. The correlation coefficient estimation procedure was used to identify the uncertain parameters that exhibited the most and least impact on the output uncertainty. These capabilities collectively are able to assist a user consider and study the reliability or robustness of alternative SWM strategies.

While this study demonstrates the applicability of the proposed approach via an illustrative case study, more investigation is needed. For example, only a small subset of input parameters was considered as uncertain. It would be necessary to extend this to the large set of ISWM DST input parameters. Through such an expanded study, one could identify the input parameters that most affect the model outputs. This is critical in efficiently improving the input data quality towards minimizing the output uncertainty. Further study is also needed to investigate the applicability of the proposed approach to a broader range of municipalities with different site characteristics and scenario definitions.

LIST OF REFERENCES

[1] Barlaz, M.A., Brill, E.D., Kaneko, A., Nishtala, S.R., Piechottka, H.R., Ranjithan, S.R. (1995). *"Integrated Solid Waste Management: 1.Mathematical Modeling"*. Proceedings of the Second Congress on Computing in Civil Engineering, ASCE, Atlanta, Georgia, June 5-8, 1995, pp. 1150-1157.

[2] Barlishen, K. D. and Baetz, B. W. (1996). *"Development of a decision support system for municipal solid waste management systems planning."* Waste Management & Research. Vol. 14, pp. 71-86.

[3] Brill, E.D. Jr., Chang S., and Hopkins, L.D. (1982). "*Modeling to generate alternatives: The HSJ approach and an illustration using a problem in land use planning."* Management Science.Vol.28, No.3, pp.221-235.

[4] Chang, N. and Lu, H.Y. (1997). *"A new approach for long term planning of solid waste management systems using fuzzy global criterion."* Journal of Environmental Science Health. Vol. A32, No. 4, pp. 1025-1047.

[5] Chang, N., Lu, H.Y., and Wei, Y.L. (1997b). *"GIS technology for vehicle routing and scheduling in solid waste collection systems."* ASCE Journal of Environmental Engineering. Vol. 123, No. 9, pp. 901-910.

[6] Harrison, K. W., R. D. Dumas, E. Solano, M. A. Barlaz, E. D. Brill, and S. Ranjithan, (2001). *"A Decision Support System for Development of Alternative Solid Waste Management Strategies with Life-Cycle Considerations,"* ASCE Journal of Computing in Civil Engineering, vol. 15(1), pp. 44-58, 2001

[7] Hokkanen, J. and Salminen, P. (1997). *"Choosing a solid waste management system using multicriteria decision analysis."* European Journal of Operational Research. Vol. 98, pp. 19-36.

[8] Jacobs, T.L. and Everett, J.W. (1992). *"Optimal scheduling of consecutive landfill operations with recycling."* ASCE Journal of Environmental Engineering. Vol. 118, No. 3, pp. 420-429.

[9] Kaneko, A. (1995). *"Solid Waste systems analysis and Landfill Utilization Policy."* North Carolina State University, Department of Civil Engineering: Ph. D. Dissertation.

[10] Karagiannidis, A. and Moussiopoulos, N. (1997). *"Case Study: Application of ELECTRE III for the management of municipal solid wastes in the Greater Athens Area."* European Journal of Operations Research. Vol. 97, pp. 439-449.

[11] Kosmicki, B. (1997a). *"Evaluation of Alternative Solid Waste Management Strategies in the Presence of Uncertainty."* North Carolina State University, Department of Civil Engineering: M.S. Thesis.

[12] Lawver, R., and Lund, J.; *"Least-cost replacement planning for modular construction of landfills."* Journal of Environmental Engineering, 1995. Vol.121, No.3, pp.203-213.

[13] Liebman, J.C., Male, J.W., and Wathne, M. (1975). *"Minimum cost in residential refuse vehicle routes."* ASCE Journal of the Environmental Engineering Division. Vol. 101, No. EE3, pp. 399-412.

[14] Lund, J.R., Tchobanoglous, G., Anex, R.P., and Lawver, R.A. (1994). *"Linear programming for analysis of material recovery facilities."* ASCE Journal of Environmental Engineering. Vol. 120, No 5, pp 1082-1094.

[15] Morgan, G.M., Henrion, M.; "*Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis"*. Cambridge University Press, New York, New York 1990.

[16] Nishtala, S. (1995). *"Design and analysis of material recovery facilities in an integrated solid waste management system."* North Carolina State University, Department of Civil Engineering: Master of Science Thesis.

[17] Powell, J. (1997). *"The evaluation of waste management options."* Waste Management & Research. Vol. 14, pp. 515-526.

[18] Powell, J., Craighill, A., and Brisson, I. (1996). *"The lifecycle assessment and valuation of waste management options: A UK study"* Proceedings of the Air and Waste Management Association, 89th Annual Meeting & Exhibition, June 23-28, 1996, Nashville, Tennessee. 96-WP78B.02.

[19] Ranjithan, S.R., Barlaz, M.A., Brill, E.D., Fu S.Y, Kaneko A., Nishtala, S.R., Piechottka, H.R. (1995). *"Integrated Solid Waste Management: 2. Decision Support System".*_Proceedings of the Second Congress on Computing in Civil Engineering, ASCE, Atlanta, Georgia, June 5-8, 1995, pp. 1158-1165.

[20] Solano, E. (1996). *"Life Cycle Assessment of Municipal Solid Waste Management Alternatives: An Integrated Optimization Model."* North Carolina State University, Department of Civil Engineering: M. S. Thesis.

[21] Solano, E. (1999). *"Integrated solid waste management alternatives in consideration of economic and environmental factors: a mathematical model development and evaluation"*, North Carolina State University, Department of Civil Engineering: Ph.D. Dissertation.

[22] Solano, E., R. D. Dumas, K. W. Harrison, S. Ranjithan, M. A. Barlaz, and E. D. Brill, (2001b). *"Life Cycle-Based Solid Waste Management – 2. Illustrative Applications,"* ASCE Journal of Environmental Engineering (accepted for publication with revisions)

[23] Solano, E., S. Ranjithan, M. A. Barlaz, and E. D. Brill, (2001a*). "Life Cycle-Based Solid Waste Management – 1. Model Development,"* ASCE Journal of Environmental Engineering (accepted for publication with revisions)

[24] USEPA (1997). *"Characterization of Municipal Solid Waste in the United States: 1996 Update."* EPA/530-R-97-015, Office of Solid Waste, U.S. Environmental Protection Agency, Washington, D.C.