OPTIMAL LOCATION OF CONTROL VALVES IN PIPE NETWORKS BY GENETIC ALGORITHM[a]

Discussion by Giuseppe Pezzinga[4] and Roberto Gueli[5]

The discussers read this paper with considerable interest. The authors' proposed use of a genetic algorithm for optimal valve location is very interesting. With reference to the example network studied by the authors, the discussers used genetic algorithms to determine the valve openings that minimize leakage (Gueli and Pezzinga 1998). The work of the discussers differs from that of the authors also in the method used in the search for the optimal valve locations. This method is based on the approach proposed by Pezzinga (1994). In particular, the optimal location of valves considering leakage minimization in 24 hours is determined. Futhermore, it is assumed that each optimal combination of N_V valves contains the optimal combination of $N_V - 1$ valves. This hypothesis, which obviously is not rigorous but only reasonable, allows one to reduce drastically the number of valve combinations to be tested.

[a]November/December 1997, Vol. 123, No. 6, by L. F. R. Reis, R. M. Porto, and F. H. Chaudhry (Paper 11658).

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Complete enumeration with no repetitions would require one to examine the following number of combinations:

$$C_{N_V} = \frac{\prod_{i=1}^{N_V} (N_P - i + 1)}{N_V!} \tag{15}$$

whereas the previous hypothesis allows one to consider the following number of combinations:

$$C_{N_V} = N_V N_P - \frac{N_V(N_V - 1)}{2} \tag{16}$$

This number is expected to be smaller than the number of optimization calculations required by the authors' procedure—that is, equal to the product of the number of generations times the population size.

The aforementioned hypotheses were used to search for the best combination of valves, determining the optimal valve openings by means of Pezzinga's (1994) nonlinear optimization algorithm, a slightly modified version of that of Jowitt and Xu (1990). The results of the search for the best first and second valves are summarized in Fig. 14, where the reduction in the daily leaked volume, ΔV_L, as a percentage of the leaked volume without control is shown. However, in some cases, this algorithm does not converge because of oscillating solutions. This consideration suggested testing genetic algorithms for the determination of valve openings.

The discussers used both an algorithm based on a binary coding of the problem parameters and an algorithm with floating point coding, working directly on the real values of these parameters (Michalewicz 1994). The main difference between the binary algorithm and the floating point algorithm is in the genetic operators. The genetic operators of the binary algorithm are similar to those described by the authors. The float-

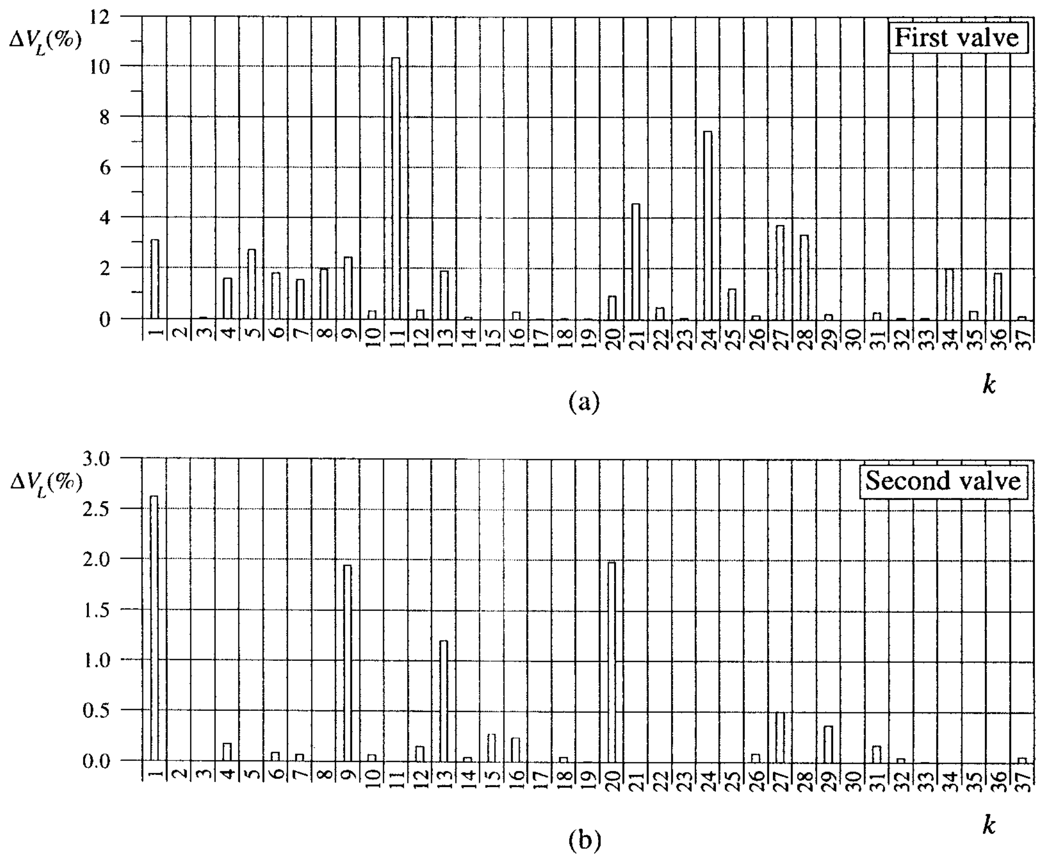

FIG. 14. Saved Leakage as Function of (a) First and (b) Second Valve Location

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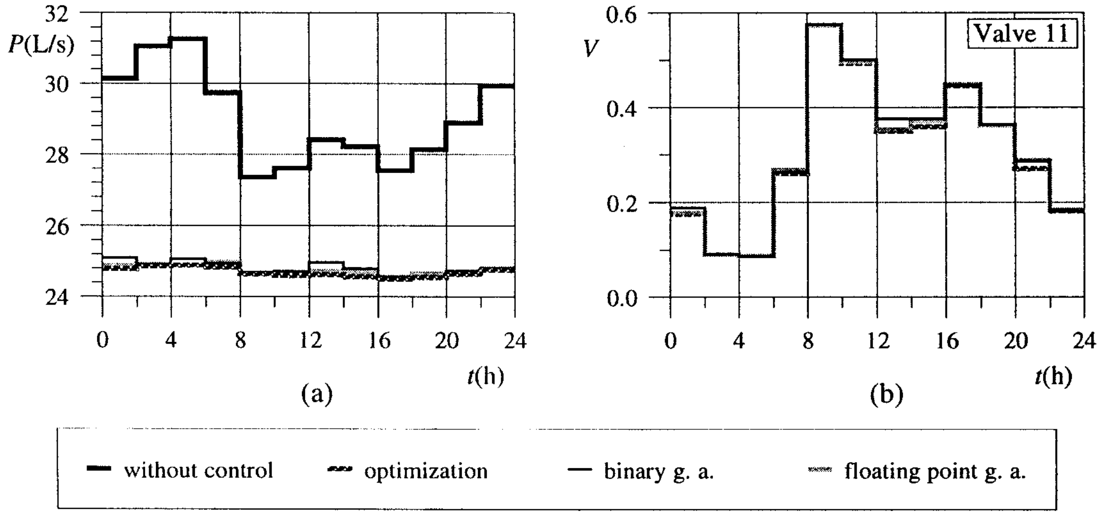

FIG. 15. Comparisons of (a) Leakage and (b) Valve 11 Opening for 1-11-20

ing point algorithm operators are briefly described here. The crossover operator used is defined as a linear combination, using a weight coefficient in the range between 0 and 1, of the parameters beyond the crossover point, randomly selected, in the vectors representing the solution. As a particular case, it is possible to make a linear combination of the whole vectors (Michalewicz 1994). The three mutation operators used work as follows. The first operator, called uniform mutation, consists in changing randomly, with a certain probability, the value of a single parameter in a new value, randomly selected in the acceptable range. In the second operator, called boundary mutation, the selected parameter can assume only the two boundary values of the acceptable range with equal probability (this is very useful in the examined problem, where the solution often contains the complete closing or opening of some valves). The third operator is similar to the first, but the random variation occurs in a range more and more contracting with generations, and is responsible for a fine-tuning of valve openings (Michalewicz 1994). More details on the genetic algorithms and operators used can be found in Gueli and Pezzinga (1998).

Preliminarily, the binary algorithm was tested, with different options. The final choice was to consider both the ‘‘death penalty’’ option, which means to exclude in the next generation solutions that do not respect the heads constraints, and ‘‘elitism,’’ which means to reply in the next generation the best solution. The influence on convergence of the individual bit number was also examined. It was found that, among 8, 12, and 16 bits, the 12 bit option gives the best results in 300 generations. In fact, if the bit number is too small, the algorithm converges rapidly, but the precision is not sufficient to represent adequately the real parameter (in this case, the valve parameter); if the bit number is too high, the convergence of the genetic algorithm is slower. The genetic algorithm allows one to obtain results when the nonlinear optimization algorithm does not converge. In particular, with the nonlinear optimization algorithm, it is not possible to obtain complete results with valves 5-11, 11-34, and 11-36, because of oscillating solutions in a few two hour intervals. The leaked volumes computed by the binary algorithm are V_L = 2,247 m^3 for 5-11; V_L = 2,245 m^3 for 11-34; and V_L = 2,247 m^3 for 11-36. The previous three combinations of two valves do not give better results than 1-11 (V_L = 2,181 m^3 by nonlinear optimization, V_L = 2,188 m^3 by binary genetic algorithm), which was found to be the best combination of two valves on the base of the nonlinear optimization algorithm, as already shown in Fig. 14.

Subsequently, the floating point algorithm was applied and compared with the binary algorithm. The comparison shows that the floating point algorithm allows one to obtain a solution slightly better than that obtained by the binary algorithm. This is probably due to the poor subdivision of the valve parameters range determined by binary coding. However, the binary algorithm normally achieves the solution earlier than does the floating point algorithm. More details on these results can be found in Gueli and Pezzinga (1998).

The values of the leaked discharge and the valve parameters computed by both genetic algorithms are practically equal to those computed by the nonlinear optimization algorithm. In Fig. 15, for the case of valves 1-11-20, the computed values of the leaked discharge and the valve 11 parameter are compared.

In Fig. 16, the daily leaked volumes V_L computed by the nonlinear optimization algorithm and the genetic algorithms are shown as a function of the valve number N_V. The results of the presented procedure lead one to place the first valve on pipe 11, the second on pipe 1, the third on pipe 20, the fourth on pipe 13, the fifth on pipe 27, and the sixth on pipe 5. It can be noted that by increasing the number of valves, the benefit of leakage reduction decreases, becoming practically negligible for the fourth valve in the examined network.

Some differences between the authors' and the discussers' results exist. According to the authors, the best combination of three valves is 1-11-29. Conversely, the results of the discussers show that the best combination of three valves is 1-11-20, obtained by nonlinear optimization algorithm and confirmed by genetic algorithms. However, it should be said that reservoir ground levels, not specified in the paper by Jowitt and Xu (1990), were chosen equal to 40 m, and this could make some difference in the results.

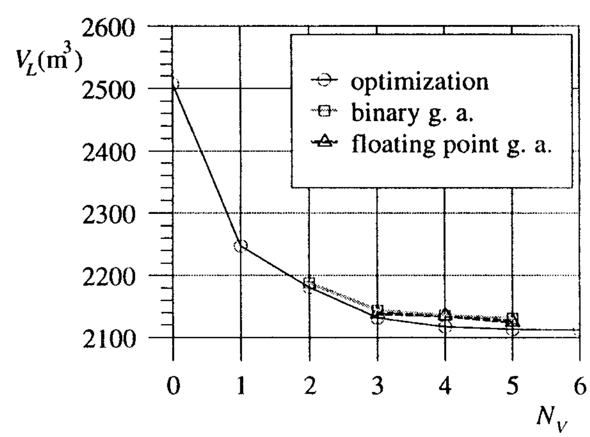

FIG. 16. Leaked Volume as Function of Valve Number

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Finally, it would be interesting to know more about the authors' experience on convergence of the valve opening optimization model. The work of the discussers shows that both tested genetic algorithms present good features in terms of robustness and efficiency and can be used as an alternative to a nonlinear optimization algorithm for the solution of the valve opening problem.

APPENDIX. REFERENCES

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Closure by L. F. R. Reis,[6] R. M. Porto,[7] and F. H. Chaudhry[8]

The discussers have presented interesting comments on our paper. They report on their work on optimal location of valves employing different optimization techniques. The writers also observed, by comparison between the successive optimal valve location combinations, that the hypothesis adopted by the discussers held during our complete simulations. The writers consider the assumption that each optimal combination of N_V valves contains the optimal combination of $N_V - 1$ valves to be a good working hypothesis, which reduces drastically the number of combinations to be tested, as demonstrated by the discussers.

Regarding the performance of the Jowitt-Xu model for optimal valve openings, the writers also observed that it did not converge for the combinations 5-11, 11-34, and 11-36 for some demand levels in the network studied. From this point of view, their decision to use genetic algorithms for the determination of valve openings is quite justified. However, there is a price to pay in terms of computational time when a search method replaces a mathematical optimization program—in this case, the linear programming method.

The differences between the results on optimal locations presented by the writers for the three valve case (1-11-29) and the valve combination obtained by the discussers (1-11-20) may very well be due to their fixing reservoir ground levels at 40 meters. However, it should be noted from Tables 1 and 6 that these two combinations compete very closely with each other and have nearly the same reduction of water losses. Besides, the writers' results are not based on the consideration of demand during a 24 hour period.

The writers close this discussion recognizing the contributions made by the discussers in their work to the problem of optimal location of valves by genetic algorithms, opening new possibilities for the study of leakage reduction in pipe networks.

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MULTIOBJECTIVE ZONE TP REDUCTION ANALYSES FOR AN OFF-STREAM RESERVOIR[a]

Discussion by L. G. Tong,[3] and G. H. Huang[4]

The authors present a deterministic multiobjective linear programming model for ''improving comparison and evaluation of non-point source pollution control strategies.'' They have done a reasonable job in presenting the model for solving a practical problem. However, the discussers feel that a few points need to be discussed and clarified before the proposed model can be advocated.

GENERAL MODELING APPROACH

In the proposed model, the only decision variables are X_{ik} (the fraction of phosphorus fertilizer reduction for crop k in watershed i). These variables are directly related to the phosphorus level in the reservoir. However, many other human activities may affect the phosphorus level, including the cropping area, livestock husbandry, soil conservation practices, land use plans, and forest coverage. Consequently, a good decision for phosphorus-fertilizer control may not be good for the entire watershed system, since many other activities were not considered in the systems analysis. For example, to reduce phosphorus concentration in the reservoir, one can either reduce the fertilizer application per unit cropping area or reduce the total cropping area. Generally, phosphorus pollution control is not merely a matter of phosphorus fertilizer application; rather, it is related to many environmental and socio-economic factors as well as their interactive relationships.

CONSTRAINTS

In an agricultural system, cropping and livestock husbandry are related to the water quality objective of the reservoir. Crops need water and generate non-point source pollutants from fertilizer application. Livestock husbandry brings economic benefits, but it also discharges wastewater to the reservoir. For such a complicated system, more constraints for defining relationships between human activities and system conditions/objectives may have to be considered, such as those related to agricultural production and water quality management. For example, more constraints for the authors' model (3) are suggested as follows:

1. Phosphorus loss constraints:

$$\sum_k (1 - X_{ik})P_{ik} \le TP_i \qquad \forall i \tag{6}$$

where TP_i = maximum allowable phosphorus loss from agricultural activities in watershed i.

2. Production loss constraints:

$$\sum_k W_k(P_{ik}X_{ik}) \le A_i \qquad \forall i \tag{7}$$

$$\sum_i W_k(P_{ik}X_{ik}) \le B_k \qquad \forall k \tag{8}$$

[a]July/August 1997, Vol. 123, No. 4, By Jehng-Jung Kao and Cheng-Hsien Tsai (Paper 12201).

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where A_i = maximum allowable production loss from agriculture activity in watershed i; and B_k = maximum allowable production loss for crop k in the entire region.

OBJECTIVE FUNCTIONS

The authors used total production loss (due to phosphorus fertilizer reduction) to represent the system cost that is to be minimized. In fact, the reduced fertilizer application will result in both a loss of agricultural production and a saving of fertilizer purchasing and application. Therefore, this system objective should be a net production loss, changing the original objective function to:

$$\min \sum_i \sum_k W_k P_{ik} X_{ik} - \sum_i \sum_k C_k P_{ik} X_{ik} \qquad \text{(cost)} \tag{9}$$

where W_k = production loss per unit phosphorus fertilizer reduction for crop k; P_{ik} = amount of phosphorus fertilizer application for crop k in watershed i; C_k = cost of fertilizer purchasing/application for crop k; and X_{ik} = fraction of phosphorus fertilizer reduction for crop k in watershed i.

UNCERTAINTIES

Many parameters in the proposed model are uncertain, including W_k, P_{ik}, and C_k in (9). The authors assumed deterministic values for all of these parameters, as shown in Tables 2 and 3, to make it possible to apply a deterministic model. To obtain the two tables, they had to use either mean values or middle values to represent these uncertain parameters. However, for a system with many uncertain factors, this type of approximation may lead to loss and/or misuse of information. Therefore, application of more effective approaches, such as fuzzy or stochastic programming, for the study problem is highly recommended. For example, the ''watershed control strategy'' model (discussed by the authors on page 212) can be converted to an inexact multiobjective programming problem as follows:

$$\min \sum_i \sum_k W_k^{\pm} P_{ik}^{\pm} X_{ik}^{\pm} - \sum_i \sum_k C_k^{\pm} P_{ik}^{\pm} X_{ik}^{\pm} \quad \text{(Cost)} \tag{10}$$

$$\max \sum_i IP_i \sum_k P_{ik}^{\pm} X_{ik}^{\pm} \quad \text{(Load reduction)} \tag{11}$$

$$\min \sum_i \sum_k U_{ik} + V_{ik} \quad \text{(Equity)} \tag{12}$$

Subject to:

$$0 \le X_{ik}^{\pm} \le 1 \quad \forall i, \forall k \tag{13}$$

$$\sum_k (1 - X_{ik}^{\pm}) P_{ik}^{\pm} \le TP_i \quad \forall i \tag{14}$$

$$\sum_k W_k^{\pm} (P_{ik}^{\pm} X_{ir}^{\pm}) \le A_i \quad \forall i \tag{15}$$

$$\sum_i W_k^{\pm} (P_{ik}^{\pm} X_{ik}^{\pm}) \le B_k \quad \forall k \tag{16}$$

$$\left(\sum_i \sum_k X_{ik}^{\pm} \right) \Big/ N = X_{\mathrm{AVE}}^{\pm} \tag{17}$$

$$X_{ik}^{\pm} - U_{ik} + V_{ik} - X_{\mathrm{AVE}}^{\pm} = 0 \quad \forall i, \forall k \tag{18}$$

$$X_{ik}^{\pm} \in F_d \quad \forall i, \forall k \tag{19}$$

where $W_k^{\pm}$, $P_{ik}^{\pm}$, $X_{ik}^{\pm}$, $C_k^{\pm}$, and $X_{\mathrm{AVE}}^{\pm}$ are interval parameters/variables. For example, letting W_k^- and W_k^+ be lower and upper bounds of $W_k^{\pm}$, respectively, we have $W_k^{\pm} = [W_k^-, W_k^+]$. The above model can be solved through either a fuzzy multiobjective programming or an inexact-fuzzy multiobjective programming method (Dutta et al. 1992; Wu et al. 1997).

SUMMARY

Generally, environmental quality in a reservoir is related to a number of environmental resources and socio-economic factors, which vary temporally and spatially. There are also numerous interactions between these factors. Therefore, good decisions for a subsystem (e.g., those related to phosphorus fertilizer application) may not really be good for the entire system. Thus, approaches that can integrate a variety of system components within a general modeling framework instead of examine them in isolation would be helpful for generating more realistic decision alternatives (Kainuma et al. 1990; Wu et al. 1997). This type of approach should be able to effectively reflect interactive, multiobjective, dynamic, and uncertain features of the study system. The outputs would be interpreted to generate desired decision alternatives for a number of human activities as well as related environmental management strategies and policies.

APPENDIX. REFERENCES

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Closure by Jehng-Jung Kao[5]

The writer deeply appreciates the valuable comments provided by the discussers. From the perspective of developing a general model, the writer agrees with most of the points raised by the discussers to enhance the proposed model. However, the writer wants to further clarify the underlying modeling concept of the study. The model is mainly developed to compare three zone fertilizer control strategies for agricultural activities instead of precisely analyzing the entire phosphorus reduction response within a reservoir and its entire watershed. The model attempts to compare, among three strategies:

1. Possible amounts of phosphorus load reduced
2. Possible financial impacts on the farmer
3. How fair each strategy is

The proposed model provides information on a control strategy with respect to its effectiveness, negative impacts on the farmer, and fairness. Such a model is definitely not a general or comprehensive watershed management model. The fertilizer control strategy is not the only strategy implemented for the studied watershed to reduce phosphorus loads. In addition to testing various best management practices (BMPs) for both soil conservation and water quality improvement, a long-term land use alternation plan that would subsidize the farmer is also being studied. These issues are, however, beyond the scope of the study.

The purpose of a model must be clearly defined before developing it. A general model, although attractive, may be too complex, impractical, and occasionally misleading. A general model may require too much effort in evaluating and preparing data or issues that contribute only a limited amount of additional information to reach a proper decision. For instance, a

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detailed evaluation of areas such as forest coverages is unnecessary for the study because (1) the model is primarily used for comparing different zone fertilizer control strategies; and (2) forest coverages generally do not have fertilizer application. As to the discussers' comment regarding reducing the unit fertilizer application with an unchanged cropping area or reducing the cropping area with an unchanged unit fertilizer application, both are acceptable for the model because only the total amount of generated phosphorus load is of relevant interest.

Although the additional constraints suggested by the discussers can be added, they are unnecessary for this study. The phosphorus reduction and production loss are mainly used to compare the financial impact on the farmer under various control strategies. If the solution shows a requirement of some phosphorus reduction and production loss, then the watershed authority should either consider compensating the farmer with some subsidy program or simply buy the land from the farmer. Without the constraints, the maximum allowable phosphorus reduction is actually equivalent to the total removal of all cropping areas within a subwatershed, which expresses an extremely high impact on the farmer. Such a circumstance may rarely occur in the United States or Canada, but in Taiwan, the watershed authority may simply buy the farmer's land, if it is necessary. Setting the maximum allowable loss is therefore not necessary for this study. Any decision made by the watershed authority should be primarily based on the maximum allowable water quality degradation for the reservoir.

The writer appreciates the discussers' suggestion of adding fertilizer cost reduction into the cost objective. We do not have detailed information regarding this matter, and it was therefore not included. However, the writer assumes that adding the additional cost item would not alter the comparison because the fertilizer cost reduction is approximately proportional to the amount of fertilizer reduced. It will change the value of the objective, but not the comparison; i.e., the order of the three control strategies based on the cost objective may still be the same. The cost objective serves only as an approximation of the financial impact on the farmer for comparison purposes rather than to estimate the precise cost. Actually, if the goal is to analyze the precise cost, the proposed model has some other problems. For example, the assumption of loss, which is linearly proportional to the fertilizer application, may underestimate the cost when the fertilizer application reduction becomes large. Additional cost reductions such as fertilizer application expense and production transportation expense may also need to be included. Although it may be possible to formulate a complex precise cost function which can precisely evaluate all related factors after a significant effort spent for data collection and analysis, it is still unlikely that this may alter the comparison.

The final issue raised by the discussers, that of uncertainty, is essential for a decision model and definitely should be explored in the future. However, the writer would like to make further comments on analyzing uncertainty and using a fuzzy- or grey-based programming approach for such a comparison study strategy.

Analyzing uncertainty is valuable only when the system uncertainty is sufficient to alter the comparison. For example, if the difference of an evaluated objective, e.g., cost, between two solutions is significant, e.g. 30%, and the uncertainty may alter the solution by at most 10%, uncertainty analysis is unnecessary because it will not alter the comparison. In applying a fuzzy- or grey-abased programming approach, results obtained from such an uncertainty analysis may be impractical if (1) the used membership functions or grey numbers require too much subjective determination; or (2) one does not have too much knowledge of the occurrence possibility for the range of parameter values.

The above discussion, however, does not imply that precise cost estimation and uncertainty analysis are unimportant. Instead, the writer intends to emphasize that an environmental systems analyst should not use a complex model if a simpler model can adequately provide appropriate information for further analysis.

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