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A GREY FUZZY MULTIOBJECTIVE PROGRAMMING APPROACH FOR THE OPTIMAL PLANNING OF A RESERVOIR WATERSHED. PART A: THEORETICAL DEVELOPMENT

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Abstract—The conflict among environmental and economic goals is a constant problem that always bothers the decision makers in regional planning. Besides, the uncertainties regarding the fuzzy goals in decision making and the impreciseness of parameter values in a system always create additional difficulties in management planning and analysis. This paper develops a new approach, a grey fuzzy multiobjective linear programming (GFMOLP) method, for the evaluation of sustainable management strategies for systems analysis. In particular, it demonstrates how uncertain messages of the planning objectives can be quantified by specific membership functions and combined through the use of grey numbers in a multiobjective analytical framework. It is verified that such an approach can successfully reflect system complexity and generate more flexible and robust management policies. Copyright © 1996 Elsevier Science Ltd

Key words—water resources systems planning, multiobjective programming, fuzzy sets theory, grey systems theory

INTRODUCTION

Many studies have been focused on multiobjective land-use planning under various conditions, including those applications in the planning of the industrial complex, watershed, river basin, or small island (Goicoechea and Duckstein, 1976; Van and Nijkamp, 1976; Das and Haimes, 1979; Wright *et al.*, 1983; Glover and Martinson, 1987; Ridgley and Giambelluca, 1992; Leone and Marini, 1993). Chang *et al.* (1995b) have applied multiobjective linear programming techniques to explore an integrated optimal planning for the carrying capacity of land uses and assimilative capacity of reservoir water quality. Decision making for various land development programs, however, is a complicated human activity, and the uncertainties involved in decision analysis may present very different characteristics. The random character of the natural processes governing water resources, the estimation errors in parameters of water quality models, and the vagueness of planning objectives and constraints are all possible sources of uncertainty (Beck, 1987). None of the above research has discussed the uncertainties in the process of environmental planning.

The fuzzy sets theory, described by the membership function, is identified as an alternative approach to supplement the vagueness description of the planning goals and the uncertainties involved in the parameter values, respectively. In the last two decades, fuzzy sets theory has received wide attention in the field of environmental planning and management (Sommer and Pollatschek, 1978; Esogbue and Ahipo, 1982; Bogardi *et al.*, 1983; Jowitt, 1984; Koo and Shin, 1986; Slowinski, 1986; Yi and Zhang, 1989; Koo *et al.*, 1991; Xiang *et al.*, 1992; Julien, 1994; Chang and Wang, 1996a; Chang *et al.*, 1995a, b). Furthermore, the technique of grey mathematical programming, in which the parameters are illustrated by the intervals, have also been applied to planning many environmental systems (Huang *et al.*, 1992, 1993, 1994a, b; Huang and Moore, 1993; Chang and Wang, 1996b). In the case of water quality modelling, sufficient information on parameter values is usually not available to assess their probability distributions. It thus appears that the parameter values related to the environmental or economic factors may frequently encounter the grey types of message, while the imprecise objectives proposed by the decision makers are much more adequately described by the prespecified fuzzy membership functions.

A new methodology—the grey fuzzy multiobjective linear programming (GFMOLP) model—and its solution procedure are thus developed in this paper. It specifically shows how the grey messages related to

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the input parameter values and the fuzzy goals pertaining to the decision maker's aspiration levels are simultaneously communicated into the multiobjective optimization process, and creates a set of more flexible optimal solution.

DEVELOPMENT OF THE GFMOLP MODEL

A fuzzy set A can be characterized by a membership function which assigns to each object of a domain its grade of membership in A (Zadeh, 1965). The more an element or object can be said to belong to a fuzzy set A, the closer to 1 is its grade of membership. The focus of fuzzy sets theory is thus placed upon its nonstatistical characteristics in nature that refers to the absence of sharp boundaries in the information. Various types of linear and nonlinear functions were suggested as fuzzy membership functions in the literature, which can be used to support the fuzzy analytical framework, although the fuzzy description is hypothetical and membership values are subjective. Nevertheless, the advantages of the incluion of such linguistic expressions and the adoption of soft computing techniques would present a new realization of decision making in human activities. Since the goal of the fuzzy mathematical programming is to optimize the fuzzy objective and constraints simultaneously, a decision in a fuzzy environment can thus be defined by the intersection operator for those membership functions corresponding to fuzzy objectives and constraints (Zimmermann, 1985). The use of the fuzzy multiobjective linear programming (FMOLP) model for solving the reservoir watershed planning issue was established by Chang *et al.* (1995b).

On the other hand, grey systems theory was developed by Deng in 1984 in China (Deng, 1984), in which all systems are divided into three categories, including the white, grey, and black parts. While the white part shows completely certain and clear messages in a system, the black part has totally unknown characteristics (Deng, 1984). Hence, the messages released in the grey part are in between, that represents the absence of sufficient intrinsic information between two sharp boundaries. Therefore, a grey number $\otimes(a)$ in the grey system may be delineated by a closed interval with upper and lower limits $[\underline{\otimes}(a), \bar{\otimes}(a)]$. Such an illustrative method supplements the expression of system uncertainties whenever the probability density and membership functions cannot be fully identified. Therefore, the grey expression with the format of a closed interval for each uncertain parameter value may exhibit a concise way of transforming the uncertainty through the optimization process and obtaining a set of flexible solutions.

Many approaches were used to illustrate the impreciseness/uncertainties in mathematical programming models. But little effect was achieved in search of the global uncertain impacts in the process of optimization. For instance, stochastic programming requires large size of data for identification of the probability distribution, but, in many cases, imprecise information cannot be fully identified by conventional probability theory. In addition, although sensitivity analysis used in the conventional linear programming framework usually performs the major role to explore the uncertainties of coefficients, it cannot directly and simultaneously reflect the uncertain impacts, involved in a number of input parameters, in a set of optimal solutions. Furthermore, in the conventional mathematical programming analysis, when the extremes and the directional influence of the extremes are known, the scenario approach may generate equally likely scenarios. Suppose there are ten scenarios and the objective is to be minimized. If the ten scenarios are considered either equally likely or will occur with unknown but positive probability, then decision making could focus on the best alternative in order to minimize the maximum value the objective takes on over all ten scenarios. In reality, such operation is frequently used to minimize the maximum cost or maximum impact no matter which scenario actually occurs. But the preparation of these scenarios are time-consuming.

In real-world applications, it is found that the grey uncertainties involved in the input parameter values can propagate through the optimization analysis, which may further perturb the accuracy of the optimal solution and decrease the possibility of implementation. The fuzzy programming approach is thus found to be unable to communicate such a type of uncertain input information directly into the optimization processes and solutions. Therefore, the techniques of grey and fuzzy mathematical programming would be better combined together in the multiobjective programming models to present a more realistic and flexible mathematical programming structure. The following emphasis will be placed upon how to combine the grey and fuzzy expressions in a multiobjective analytical framework.

In a GFMOLP model, the left-hand side coefficients and the right-hand side stipulations in the constraints as well as the tolerance interval of aspiration levels in the objective function are defined as grey numbers, since some of those parameters in the systems are frequently lack of knowledge regarding how to specify the exact membership functions. Hence, the use of grey systems theory to improve the FMOLP model may present at least four more contributions: (1) grey uncertainties embedded in the model parameters can be directly reflected and communicated into the optimization processes; (2) the variation or vagueness of the decision maker's aspiration level (i.e., denoted as the intermediate control variables in the model) in the FMOLP model can further be narrowed down and thereby generate a more confident solution set for policy decision making; (3) regardless of the orientations of the decision maker's aspiration level (i.e., maximization or minimization of specific targets), each objective or goal may have its own independent membership function which is simultaneously described by its grey message of tolerance such that a high level trade-off in the optimization process is achievable; and (4) the GFMOLP configuration would automatically generate the most favorable optimal solution by a set of closed intervals for all the decision variables. It is not necessary to search for the satisfactory solution in a set of noninferior solutions by distance-based criteria, as required by the conventional solution procedure of the deterministic multiobjective programming model (Zeleny, 1974, 1976; Cohon, 1978). The following discussion presents the theoretical structure of the GFMOLP model and its solution procedure.

In the GFMOLP models, the conventional distinction between objectives and constraints no longer applies. The problem with multiple grey fuzzy objectives and grey parameters in the constraints can be stated as finding the optimal grey fuzzy decision D in a similar manner as the case in the pure fuzzy environment. Two different groups of fuzzy objectives may be separately formulated, in which a nondecreasing and a nonincreasing linear membership functions with grey tolerance intervals are assumed for those objectives to be maximized and minimized, respectively. In reality, these expressions must correspond to the grey fuzzy implications of "the greater, the better under a grey upper bound" or "the smaller, the better under a grey lower bound". However, each objective and constraint may have its own independent membership function, and these functions can only be identified within a range of grey tolerance level. In equation (1), the grey intermediate control variable $\otimes(\alpha)$ represents the degree of uncertainties associated with those inequalities with "smaller than or equal to" and "greater than or equal to" relationships, respectively, in the model. Max–min convolution is then achieved through the intersection of the degree of aspiration levels of corresponding objectives and the degree of approximation level of corresponding inequality constraints (Zimmermann, 1985). Thus the fuzzy objectives associated with their grey messages can be arranged as a set of goal constraints, as shown in the following first and second constraint sets in equations (2) and (3), respectively.

Furthermore, the original definitional constraints are still retained in the decision space for the max–min convolution, as shown in equations (4) and (5). In the systems analysis for environmental quality management, if a constraint is prepared for the fuzzy expression of "the level of environmental resources consumption is substantially less than a given grey limitation", it is adequate to be described by a nonincreasing linear membership function for the possible illustration of the fuzzy availability of the grey environmental resources. Such a constraint would not hold if we choose a nondecreasing linear membership function for a "less than or equal to" inequality. On the other hand, for example, if the constraint is prepared to delineate the fuzzy expression of "the minimum specific land development for sustainable yield of food product in a river basin or a reservoir watershed has to be substantially greater than a grey limitation", it is better to be described by a nondecreasing linear membership function for possible illustration of the utilization of land resources. Similarly, such a constraint would not hold if we choose a nonincreasing linear membership function for a "greater than or equal to" inequality. However, either nondecreasing or nonincreasing linear membership functions can be used for illustration of the equality constraint, since selection of the type of membership function is much more dependent on the actual physical meaning of such an expression. Equations (4) and (5) fulfill the above mathematical thinking in applications.

Overall, to build a fuzzy multiobjective programming model, the decision makers or analysts may establish aspiration levels, f_i and f_j, in advance that he or she wants to achieve for the values of the objective functions to be minimized and maximized, respectively, as well as each of the constraints modelled as a fuzzy set by a specific membership function. δ_i, δ_j, δ_k, and δ_l applied in equations (8) and (9) are the tolerance intervals associated with each corresponding linear membership function. The elements in matrices **A**, **B**, and **C** are defined as grey numbers, which might provide one of the flexibilities in the formulation of such fuzzy constraints and result in the grey fuzzy multiobjective programming model. Since a fuzzy description associated with the grey messages may constitute the grey fuzzy membership function for a global sensitivity analysis in decision making since the expression of fuzzy membership function itself is fuzzy, and the fuzzy membership value is an interval value. Hence, the configuration of those nonincreasing or nondecreasing linear membership functions with mobile grey tolerances can be viewed as the superimposed image of two similar types of fuzzy linear membership functions. The GFMOLP model is thus formulated as:

$$\max \otimes(\alpha) \tag{1}$$

subject to:

(1) constraints for the objectives to be minimized:

$$\otimes(\mathbf{C}_i^T) \otimes(\mathbf{X}) \leq \otimes(f_i) + (1 - \otimes(\alpha))[\bar{\otimes}(f_i) - \underline{\otimes}(f_i)] \qquad i = 1, \ldots, m \tag{2}$$

(2) constraints for the objectives to be maximized:

$$\otimes(\mathbf{C}_j^T(\otimes(\mathbf{X}) \geq \otimes(f_j) + \otimes(\alpha)[\bar{\otimes}(f_j) - \underline{\otimes}(f_j)] \qquad j = m+1, \ldots, m+n \tag{3}$$

(3) constraint for the "less than or equal to" grey fuzzy relationship:

$$\otimes(\mathbf{A}_k^T)\otimes(\mathbf{X}) \leqslant \otimes(\mathbf{B}_k) + (1-\otimes(\alpha))[\bar{\otimes}(\mathbf{B}_k)-\underline{\otimes}(\mathbf{B}_k)] \quad k=1,\ldots,p \tag{4}$$

(4) constraint for the "greater than or equal to" grey fuzzy relationship:

$$\otimes(\mathbf{A}_l^T)\otimes(\mathbf{X}) \geqslant \otimes(\mathbf{B}_l) + \otimes(\alpha)[\bar{\otimes}(\mathbf{B}_l)-\underline{\otimes}(\mathbf{B}_l)] \quad l=p+1,\ldots,p+q \tag{5}$$

(5) membership constraint:

$$0 \leqslant \otimes(\alpha) \leqslant 1 \tag{6}$$

(6) nonnegativity constraint:

$$\otimes(x_s) \geqslant 0, \quad \otimes(x_s) \in \otimes\mathbf{X} \quad s=1,\ldots,r \tag{7}$$

where

$$\delta_k = \bar{\otimes}(f_i)-\underline{\otimes}(f_i), \quad \delta_j = \bar{\otimes}(f_j)-\underline{\otimes}(f_j) \tag{8}$$

$$\delta_k = \bar{\otimes}(\mathbf{B}_k)-\underline{\otimes}(\mathbf{B}_k), \quad \delta_l = \bar{\otimes}(\mathbf{B}_l)\,\underline{\otimes}(\mathbf{B}_l) \tag{9}$$

$$\otimes(\mathbf{C}_i^T) = \{\otimes(c_1), \otimes(c_2), \ldots, \otimes(c_m)\} \tag{10}$$

$$\otimes(\mathbf{C}_j^T) = \{\otimes(c_{m+1}), \otimes(c_{m+2}), \ldots, \otimes(c_{m+n})\} \tag{11}$$

$$\otimes(\mathbf{X}) = \{\otimes(x_1), \otimes(x_2), \ldots, \otimes(x_r)\} \tag{12}$$

$$\otimes(\mathbf{A}_k^T) = \{\otimes(a_{ij})\} \quad i=1,\ldots,p, \quad j=1,\ldots,r \tag{13}$$

$$\otimes(\mathbf{A}_l^T) = \{\otimes(a_{ij})\} \quad i=p+1,\ldots,p+q, \quad j=1,\ldots,r \tag{14}$$

$$\otimes(\mathbf{B}_k) = \{\otimes(b_k)\} \quad k=1,\ldots,p \tag{15}$$

$$\otimes(\mathbf{B}_l) = \{\otimes(b_l)\} \quad l=p+1,\ldots,p+q \tag{16}$$

$$\otimes(f_i) = \{\otimes(f_i)\} \quad i=1,\ldots,m \tag{17}$$

$$\otimes(f_j) = \{\otimes(f_j)\} \quad j=m+1,\ldots,m+n \tag{18}$$

For grey vectors $\otimes(f)$ and $\otimes(\mathbf{B})$, and grey matrix $\otimes(\mathbf{A})$, we have:

$$\otimes(a_{ij}) = [\underline{\otimes}(a_{ij}), \bar{\otimes}(a_{ij})] \quad i=1,\ldots,p+q, \quad j=1,\ldots,r \tag{19}$$

$$\otimes(b_k) = [\underline{\otimes}(b_k), \bar{\otimes}(b_k)] \quad k=1,\ldots,p \tag{20}$$

$$\otimes(b_l) = [\otimes(b_l), \bar{\otimes}(b_l)] \quad l=p+1,\ldots,p+q \tag{21}$$

$$\otimes(f_i) = [\underline{\otimes}(f_i), \bar{\otimes}(f_i)] \quad i=1,\ldots,m \tag{22}$$

$$\otimes(f_j) = [\underline{\otimes}(f_j), \bar{\otimes}(f_j)] \quad j=m+1,\ldots,m+n \tag{23}$$

The optimal solutions for equations (1)–(7) will be:

$$\otimes(\alpha^*) = [\underline{\otimes}(\alpha^*), \bar{\otimes}(\alpha^*)] \tag{24}$$

$$\otimes(f_i^*) = [\underline{\otimes}(f_i^*), \bar{\otimes}(f_i^*)] \quad i=1,\ldots,m \tag{25}$$

$$\otimes(f_j^*) = [\underline{\otimes}(f_j^*), \bar{\otimes}(f_j^*)] \quad j=m+1,\ldots,m+n \tag{26}$$

$$\otimes(\mathbf{X}^*) = [\otimes(x_1^*), \otimes(x_2^*), \ldots, \otimes(x_r^*)] \tag{27}$$

$$\otimes(x_s^*) = [\underline{\otimes}(x_s), \bar{\otimes}(x_s)] \quad s=1,\ldots,r \tag{28}$$

Method of solution

In conventional deterministic multiobjective programming, such as compromise programming (Zeleny, 1974, 1976), noninferior solutions are frequently examined for several alternative planning scenarios using distance-based techniques. However, to obtain the optimal solution in the GFMOLP model, two submodels are required to be solved independently and the combination of optimal solutions obtained from both submodels would automatically constitute a completed set of grey fuzzy optimal solutions, as described in equations (24)–(28). Those two submodels are:

$$\max \bar{\otimes}(\alpha) \tag{29}$$

subject to:

(1) constraints for the objectives to be minimized:

$$\underline{\otimes}(\mathbf{C1}_i^T)\underline{\otimes}(\mathbf{X}) + \bar{\otimes}(\mathbf{C2}_i^T)\underline{\otimes}(\mathbf{X}) \leqslant \underline{\otimes}(f_i) + (1-\bar{\otimes}(\alpha))[\bar{\otimes}(f_i)-\underline{\otimes}(f_i)] \quad i=1,\ldots,m \tag{30}$$

(2) constraints for the objective to be maximized:

$$\bar{\otimes}(\mathbf{C1}_j^T)\underline{\otimes}(\mathbf{X}) + \underline{\otimes}(\mathbf{C2}_j^T)\underline{\otimes}(\mathbf{X}) \geqslant \underline{\otimes}(f_j) + \underline{\otimes}(\alpha)[\bar{\otimes}(f_j)-\underline{\otimes}(f_j)] \quad j=m+1,\ldots,m+n \tag{31}$$

(3) constraint for the "less than or equal to" grey fuzzy relationship:

$$\bar{\otimes}(\mathbf{A}_k^T)\underline{\otimes}(\mathbf{X}) \leqslant \underline{\otimes}(\mathbf{B}_k) + (1-\bar{\otimes}(\alpha))[\bar{\otimes}(\mathbf{B}_k)-\underline{\otimes}(\mathbf{B}_k)] \quad k=1,\ldots,p \tag{32}$$

(4) constraint for the "greater than or equal to" grey fuzzy relationship:

$$\bar{\otimes}(\mathbf{A}_l^T)\underline{\otimes}(\mathbf{X}) \geqslant \underline{\otimes}(\mathbf{B}_l) + \underline{\otimes}(\alpha)[\bar{\otimes}(\mathbf{B}_l)-\underline{\otimes}(\mathbf{B}_l)] \quad l=p+1,\ldots,p+q \tag{33}$$

(5) membership constraint:

$$0 \leqslant \bar{\otimes}(\alpha), \leqslant 1 \tag{34}$$

(6) nonnegativity constraint:

$$\underline{\otimes}(x_s) \geqslant 0, \underline{\otimes}(x_s) \in \underline{\otimes}\mathbf{X} \quad s=1,\ldots,r \tag{35}$$

and

$$\max \underline{\otimes}(\alpha) \tag{36}$$

subject to:

(1) constraints for the objectives to be minimized:

$$\underline{\otimes}(\mathbf{C1}_i^T)\,\bar{\otimes}(\mathbf{X}) + \bar{\otimes}(\mathbf{C2}_i^T)\,\bar{\otimes}(\mathbf{X}) \leqslant \bar{\otimes}(f_i) + (1-\underline{\otimes}(\alpha))[\bar{\otimes}(f_i) - \underline{\otimes}(f_i)] \quad i = 1, \ldots, m \tag{37}$$

(2) constraints for the objectives to be maximized:

$$\bar{\otimes}(\mathbf{C1}_j^T)\,\bar{\otimes}(\mathbf{X}) + \underline{\otimes}(\mathbf{C2}_j^T)\,\bar{\otimes}(\mathbf{X}) \geqslant \bar{\otimes}(f_j) + \bar{\otimes}(\alpha)[\bar{\otimes}(f_j) - \underline{\otimes}j)] \quad j = m+1, \ldots, m+n \tag{38}$$

(3) constraint for the "less than or equal to" grey fuzzy relationship:

$$\underline{\otimes}(\mathbf{A}_k^T)\,\bar{\otimes}(\mathbf{X}) \leqslant \bar{\otimes}(\mathbf{B}_k) + (1-\underline{\otimes}(\alpha))[\bar{\otimes}(\mathbf{B}_k) - \underline{\otimes}(\mathbf{B}_k)] \quad k = 1, \ldots, p \tag{39}$$

(4) constraint for the "greater than or equal to" grey fuzzy relationship:

$$\underline{\otimes}(\mathbf{A}_l^T(\bar{\otimes}(\mathbf{X}) \geqslant \bar{\otimes}(\mathbf{B}_l) + \bar{\otimes}(\alpha)[\bar{\otimes}(\mathbf{B}_l) - \underline{\otimes}(\mathbf{B}_l)] \quad l = p+1, \ldots, p+q \tag{40}$$

(5) membership constraint:

$$0 \leqslant \underline{\otimes}(\alpha) \leqslant 1 \quad \forall ij, k, l \tag{41}$$

(6) nonnegativity constraint:

$$\bar{\otimes}(x_s) \geqslant 0, \quad \bar{\otimes}(x_s) \in \bar{\otimes}\mathbf{X} \quad s = 1, \ldots, r \tag{42}$$

In the above submodels, vectors **C1** represent the terms with positive coefficients, while vectors **C2** represent the terms with negative coefficients in those objective functions to be maximized or minimized. The reason for having such a distinction of positive and negative signs in those objective coefficients is simply to achieve the goals of maximization and minimization by the correct selection of the upper or lower bounds in the grey environment. The upper and lower bounds of those decision variables would then be identified in the grey functional constraint in each submodel in order to collaborate with such an achievement in the goal constraints (Huang *et al.*, 1993). To build the grey fuzzy membership function in this analysis, a payoff table, established by solving each grey linear programming (GLP) model stepwise (Huang *et al.*, 1993), could be used to find out the most attainable bounds for each objective when overall objectives are considered simultaneously. Two submodels associated with each GLP run have to be solved sequentially in order to accomplish each pair of attainable bounds through the use of a conventional payoff table, and those attainable bounds can be used to determine the variations of input parameters in the formulation of the final GFMOLP model. Thereafter, two submodels of GFMOLP model, as in equations (29)–(42), could be solved simultaneously, by adding the conditionality constraints, $\bar{\otimes}(\mathbf{X}) \geqslant \underline{\otimes}(\mathbf{X})$, or separately through the sequential procedure, to obtain a set of grey fuzzy optimal solutions. Overall, an important point in solving the GFMOLP models is that the upper and lower bounds of objective function values obtained from a single run of each GLP model may not be the final upper and lower bounds of corresponding objective function values because of the perturbation of other objectives in the decision space.

It is therefore known that there would not have been such a set of grey intervals in the optimal solutions as above if there are no separate arrangements of those objective coefficients with positive or negative signs in each submodel of GLP and GFMOLP analysis. The flowchart of the entire solution procedure of the GFMOLP model is shown in Fig. 1. In this procedure, a concept of grey degree is introduced before the final acceptance of a set of grey fuzzy optimal solutions. As defined by Huang *et al.* (1993), the grey degree of a grey number is equivalent to its grey interval divided by its mid-value. It is expected that the grey degree generated from grey fuzzy outputs should be smaller than that of the grey solutions obtained in each single run of GLP model.

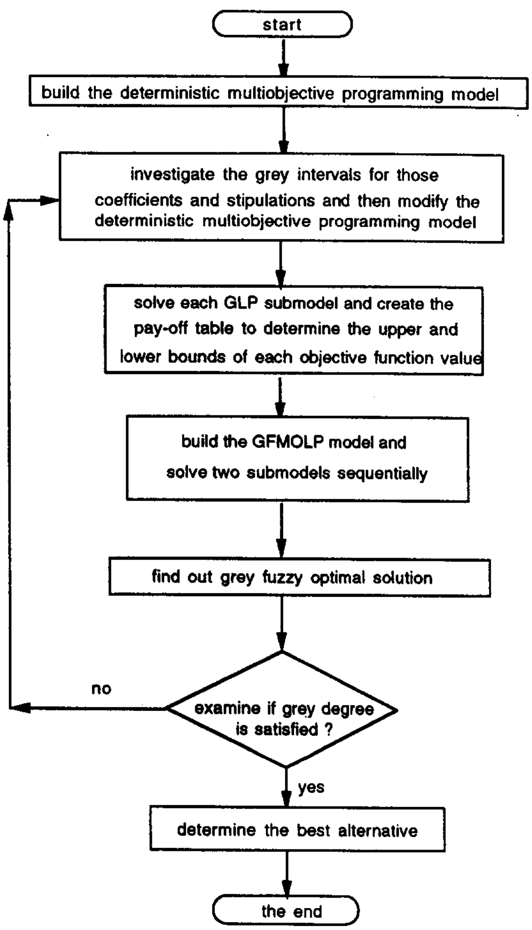

Fig. 1.

CONCLUSIONS

This analysis has presented that the proposed GFMOLP model could be an effective tool for generating a set of more realistic and flexible optimal solutions in solving real-world complicated water resource management issues. Based on such a GFMOLP methodology, in order to search for the sustainable development and management policies, the imprecise information involved in the decision making for environmental planning and management can be properly handled so that environmental impacts can be reduced to a required level, while economic benefits can be maximized simultaneously.

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