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Research Paper

Water Resource Management Using Population-Based, Dual-Criterion Simulation-Optimization Algorithms to Generate Alternatives

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ABSTRACT : *When solving complex water resources management (WRM) problems, it is often preferable to construct a number of quantifiably good alternatives that provide multiple, different perspectives. This is because WRM normally involves multifaceted problems that are riddled with incompatible performance objectives and contain inconsistent design requirements which are very difficult to quantify and capture when supporting decisions must be constructed. These alternatives need to satisfy the required system performance criteria and yet be maximally different from each other in the decision space. The approach for creating maximally different sets of solutions is referred to as modelling-to-generate-alternatives (MGA). Simulation-optimization approaches are frequently employed to solve computationally difficult problems containing significant stochastic uncertainties. This paper outlines an MGA approach for WRM that can generate sets of maximally different alternatives for any simulation-optimization method that employs a population-based search algorithm. This algorithmic approach is both computationally efficient and simultaneously produces the prescribed number of maximally different solution alternatives in a single computational run of the procedure. The effectiveness of this stochastic MGA approach for creating alternatives in "real world", water policy formulation is demonstrated using a WRM case study.*
KEYWORDS: *Water resources management, Modelling-to-generate-alternatives, Simulation-Optimization, Metaheuristics, Population-based algorithms*

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I. INTRODUCTION

Water resource managers have been confronted by water allocation problems for many decades ([1], [2]). Implementing effective water resources management (WRM) has proven to be both notoriously contentious and conflict-laden as inherent antagonism between multiple municipal, industrial and agricultural water-users has intensified. Increased population shifts and shrinking water supplies have further heightened the inter-user challenges. These antagonisms provoke additional aggravations when natural conditions become more unpredictable due to changing climatic conditions and as concern for water quantity and quality grows. Poorly-planned water allocation systems can deteriorate into more serious conflicts under detrimental river-flow and climatic conditions. In the past, increasing demand for water was met by the development of new water sources. However, significant economic and environmental costs associated with developing new water sources have rendered this approach unsustainable. Unlimited expansion of water sources is no longer the primary objective in WRM. Instead, for optimum water resource allocation, the aim becomes to improve the existing water allocation and management in a more equitable, environmentally-benign, and efficient manner by fashioning environmental policy formulation techniques for water allocation under various complexities. Such innovative strategy formulation can be extremely problematic, as many components of water systems contain substantial uncertainties. The prevalence of stochastic uncertainty renders most common decision approaches relatively unsuitable for practical implementation.

Since WRM problems generally possess all of the characteristics associated with environmental planning, WRM systems have provided an ideal backdrop for the testing of a wide spectrum of decision support techniques used in environmental decision-making [3], [4], [5]. WRM decision-making frequently possess inconsistent and incompatible design specifications that can be difficult to formulate into mathematical decision-models [1], [2], [3], [4], [5], [6]. This situation commonly occurs when final decisions must be constructed based not only upon clearly articulated specifications, but also upon environmental, political and socio-economic objectives that are either fundamentally subjective or not clearly articulated [7], [8], [9], [10]. Although "optimal" solutions can be determined for the mathematical models, whether these can be considered the best solution to the "real" problem remains somewhat questionable. Moreover, in public policy formulation, it may never be possible to explicitly convey many of the subjective considerations because there are numerous competing, adversarial stakeholder groups holding diametrically opposed perspectives. Therefore, many of the subjective aspects remain unknown, unquantified and unmodelled in the construction of any corresponding decision models. WRM policy formulation can prove even more complicated when the various system components also contain considerable stochastic uncertainties [10]. Consequently, WRM policy determination proves to be an extremely challenging and complicated undertaking [10], [11].

Within WRM decision-making, there are routinely many stakeholder groups holding completely incongruent standpoints, essentially dictating that policy-makers need to construct decision frameworks that can somehow simultaneously reflect numerous irreconcilable points of view. Under such circumstances, it is often more desirable to construct a small number of distinct alternatives that provide dissimilar viewpoints for the particular problem [3], [7]. These dissimilar solutions should be close-to-optimal with respect to the specified objective(s), but be maximally different from each other within the decision domain. Numerous approaches collectively referred to as modelling-to-generate-alternatives (MGA) have been created to address this multi-solution requirement [6], [7], [8]. The principal motivation behind MGA is the production of a set of alternatives that are "good" with respect to the specified objective(s), but are fundamentally dissimilar from each other in the decision space. Decision-makers then need to perform a subsequent evaluation of this set of alternatives to determine which specific alternative(s) most closely satisfy their specific goals. Consequently, MGA approaches are classified as decision support methods rather than as solution creation processes as assumed in explicit optimization.

Early MGA algorithms employed direct, incremental approaches for constructing their alternatives by iteratively re-running their procedures whenever new solutions needed to be generated [6], [7], [8], [9], [10]. These iterative approaches replicated the seminal MGA technique of Brill et al. [8] where, once the initial mathematical formulation has been optimized, all supplementary alternatives are produced one-at-a-time. Therefore, these approaches all employed n+1 iterations of their respective algorithms – firstly to optimize the original problem, then to construct each of the n subsequent alternatives [7], [11], [12], [13], [14], [15], [16], [17], [18].

In this paper, it is demonstrated how a set of maximally different solution alternatives can be generated by extending several earlier MGA techniques to stochastic optimization ([12], [13], [14], [15], [16], [17], [18]). The stochastic algorithm provides an MGA process that can be accomplished by any population-based mechanism. This algorithm advances earlier concurrent procedures ([13], [15], [16], [17], [18]) by permitting the simultaneous generation of n distinct alternatives in a single computational run. Specifically, to generate n maximally different alternatives, the algorithm runs exactly the same number of times that a function optimization procedure needs to run (i.e. once) irrespective of the value of n [19], [20], [21], [22], [23]. A dual-criterion, max-sum, max-min objective is employed that combines a novel data structure into the simultaneous solution approach to create an effective MGA approach. The max-sum portion of the objective endeavours to produce a maximum distance between solutions by ensuring that the total deviation between all of the variables in all of the alternatives is large. It does not preclude, however, the possibility of relatively small (or zero) deviations occurring between some of the individual variables in certain solutions. In contrast, the max-min objective seeks a maximum distance between every variable over all solutions. By considering both objectives simultaneously, the alternatives created will be as far apart as possible for all variables in general and the closest distance in the worst case between any solutions will never be less than the value obtained for the max-min objective. Furthermore, the dual-objective stochastic MGA algorithm employs a data structure that permits simultaneous alternatives to be constructed in a very computationally effective way. This data structure facilitates the above-mentioned solution generalization to all population-based methods. Consequently, this stochastic MGA algorithmic approach proves to be extremely computationally efficient. The effectiveness of this method for WRM purposes is demonstrated using a case study taken from [24] and [25].

II. MODELLING TO GENERATE ALTERNATIVES

Mathematical optimization has focused almost entirely on constructing single optimal solutions to single-objective problems or determining sets of noninferior solutions for multi-objective formulations [2], [5], [8]. While such approaches may create solutions to the mathematical models, whether these outputs are the best solutions to the "real" problems remains can be debatable [1], [2], [6], [8]. Within most "real world" decision-making environments, there are countless system requirements and objectives that will never be explicitly apparent or included in the model formulation stage [1], [5]. Furthermore, most subjective aspects remain unavoidably unmodelled and unquantified in the constructed decision models. This regularly occurs where final decisions are constructed based not only on modelled objectives, but also on more subjective stakeholder goals and socio-political-economic preferences [7]. Several incongruent modelling dualities are discussed in [6], [8], [9], and [10].

When unmodelled objectives and unquantified issues exist, non-traditional methods are required for searching the decision region not only for noninferior sets of solutions, but also for alternatives that are evidently sub-optimal to the modelled problem. Namely, any search for alternatives to problems known or suspected to contain unmodelled components must concentrate not only on a non-inferior set of solutions, but also necessarily on an explicit exploration of the problem's inferior solution space.

To demonstrate the implications of unmodelled objectives in a decision search, assume that an optimal solution for a maximization problem is **X*** with objective value Z1* [26]. Suppose a second, unquantified, maximization objective Z2 exists that represents some "politically acceptable" factor. Assume that the solution, $\mathbf{X}^{\mathbf{a}}$, belonging to the 2-objective noninferior set, exists that corresponds to a best compromise solution if both objectives could have been simultaneously considered. Although $\mathbf{X}^{\mathbf{a}}$ would be considered as the best solution to the real problem, in the actual mathematical model it would appear inferior to solution **X***, since $Z1^a \leq Z1^*$. Therefore, when unquantified components are included in the decision-making process, inferior decisions to the mathematically modelled problem could be optimal to the underlying "real" problem. Thus, when unquantified issues and unmodelled objectives could exist, alternative solution procedures are required to not only explore the decision domain for noninferior solutions to the modelled problem, but also to concurrently search the decision domain for inferior solutions. Population-based algorithms permit concurrent searches throughout a decision space and prove to be particularly proficient solution methods.

The objective of MGA is to construct a viable set of alternatives that are quantifiably good with respect to all modelled objectives, yet are as different as possible from each other within the solution space. By accomplishing this requirement, the resulting set of alternatives is able to provide truly different perspectives that perform similarly with respect to the known modelled objective(s) yet very differently with respect to various potentially unmodelled aspects. By creating these good-but-different solutions, the decision-makers are able to explore potentially desirable qualities within the alternatives that might be able to satisfy the unmodelled objectives to varying degrees of stakeholder acceptability.

To motivate the MGA process, it is necessary to more formally characterize the mathematical definition of its goals [6], [7]. Assume that the optimal solution to an original mathematical model is **X*** with corresponding objective value **Z*** = F(**X***). The resultant difference model can then be solved to produce an alternative solution, **X**, that is maximally different from **X***:

$$\text{Maximize } \Delta(\mathbf{X}, \mathbf{X^*}) = \min_i |X_i - X_i^*| \quad (1)$$

$$\text{Subject to: } \mathbf{X} \in D \quad (2)$$

$$|F(\mathbf{X}) - \mathbf{Z^*}| \leq T \quad (3)$$

where Δ represents an appropriate difference function (shown in (1) as an absolute difference) and T is a tolerance target relative to the original optimal objective value **Z***. T is a user-specified limit that determines what proportion of the inferior region needs to be explored for acceptable alternatives. This difference function concept can be extended into a difference measure between any set of alternatives by replacing **X*** in the objective of the maximal difference model and calculating the overall minimum absolute difference (or some other function) of the pairwise comparisons between corresponding variables in each pair of alternatives – subject to the condition that each alternative is feasible and falls within the specified tolerance constraint.

The population-based MGA procedure to be introduced is designed to generate a pre-determined small number of close-to-optimal, but maximally different alternatives, by adjusting the value of T and solving the corresponding maximal difference problem instance by exploiting the population structure of the algorithm. The survival of solutions depends upon how well the solutions perform with respect to the problem's originally modelled objective(s) and simultaneously by how far away they are from all of the other alternatives generated in the decision space.

III. SIMULATION-OPTIMIZATION FOR STOCHASTIC OPTIMIZATION

Finding optimal solutions to large stochastic problems proves complicated when numerous system uncertainties must be directly incorporated into the solution procedures ([26], [27], [28], [29]). Simulation-Optimization (SO) is a broadly defined family of stochastic solution approaches that combines simulation with an underlying optimization component for optimization [26]. In SO, all unknown objective functions, constraints, and parameters are replaced by simulation models in which the decision variables provide the settings under which simulation is performed.

The general steps of SO can be summarized in the following fashion ([27], [30]). Suppose the mathematical model of the optimization problem contains n decision variables, X_i, represented in the vector **X** = [$X_1, X_2, \ldots, X_n$]. If the objective function is expressed by F and the feasible region is designated by D, then the mathematical programming problem is to optimize F(**X**) subject to **X** $\in$ D. When stochastic conditions exist, values for the objective and constraints can be determined by simulation. Any solution comparison between two different solutions **X1** and **X2** requires the evaluation of some statistic of F modelled with **X1** compared to the same statistic modelled with **X2** ([26], [31]). These statistics are calculated by simulation, in which each **X** provides the decision variable settings employed in the simulation. While simulation provides a means for comparing results, it does not provide the mechanism for determining optimal solutions to problems. Hence, simulation cannot be used independently for stochastic optimization.

Since all measures of system performance in SO are stochastic, every potential solution, **X**, must be calculated through simulation. Because simulation is computationally intensive, an optimization algorithm is employed to guide the search for solutions through the problem's feasible domain in as few simulation runs as possible ([28], [31]). As stochastic system problems frequently contain numerous potential solutions, the quality of the final solution could be highly variable unless an extensive search has been performed throughout the entire feasible region. A stochastic SO approach contains two alternating computational phases; (i) an "evolutionary" module directed by some optimization (frequently a metaheuristic) method and (ii) a simulation module ([32]). Because of the stochastic components, all performance measures are necessarily statistics calculated from the responses generated in the simulation module. The quality of each solution is found by having its performance criterion, F, evaluated in the simulation module. After simulating each candidate solution, their respective objective values are returned to the evolutionary module to be utilized in the creation of ensuing candidate solutions. Thus, the evolutionary module aims to advance the system toward improved solutions in subsequent generations and ensures that the solution search does not become trapped in some local optima. After generating new candidate solutions in the evolutionary module, the new solution set is returned to the simulation module for comparative evaluation. This alternating, two-phase search process terminates when an appropriately stable system state (i.e. an optimal solution) has been attained. The optimal solution produced by the procedure is the single best solution found throughout the course of the entire search process ([32]).

Population-based algorithms are conducive to SO searches because the complete set of candidate solutions maintained in their populations permit searches to be undertaken throughout multiple sections of the feasible region, concurrently. For population-based optimization methods, the evolutionary phase evaluates the entire current population of solutions during each generation of the search and evolves from a current population to a subsequent one. A primary characteristic of population-based procedures is that better solutions in a current population possess a greater likelihood for survival and progression into the subsequent population.

It has been shown that SO can be used as a very computationally intensive, stochastic MGA technique ([31], [33]). However, because of the very long computational runs, several approaches to accelerate the search times and solution quality of SO have been examined subsequently [30]. The next section provides an MGA algorithm that incorporates stochastic uncertainty using SO to much more efficiently generate sets of maximally different solution alternatives.

IV. POPULATION-BASED DUAL-CRITERION MGA COMPUTATIONAL ALGORITHM

In this section, a data structure is employed that enables a dual-criterion MGA solution approach via any population-based algorithm [34], [35], [36]. Suppose that it is desired to produce P alternatives that each possess n decision variables and that the population algorithm is to possess K solutions in total. That is, each solution contains one possible set of P maximally different alternatives. Let $\mathbf{Y}_k$, k = 1,…, K, represent the k^{th} solution which consists of one complete set of P different alternatives. Specifically, if $\mathbf{X}_{kp}$ corresponds to the p^{th} alternative, p = 1,…, P, of solution k, k = 1,…, K, then $\mathbf{Y}_k$ can be represented as

$$\mathbf{Y}_k = [\mathbf{X}_{k1}, \mathbf{X}_{k2}, \ldots, \mathbf{X}_{kP}] . \qquad (4)$$

If X_{kjq}, q = 1,…, n, is the q^{th} variable in the j^{th} alternative of solution k, then

$$\mathbf{X}_{kj} = (X_{kj1}, X_{kj2}, \ldots, X_{kjn}) . \qquad (5)$$

Consequently, the entire population, **Y**, consisting of K different sets of P alternatives can be expressed in vectorized form as,

$$\mathbf{Y'} = [\mathbf{Y}_1, \mathbf{Y}_2, \ldots, \mathbf{Y}_K] . \qquad (6)$$

The following population-based MGA method produces a pre-determined number of close-to-optimal, but maximally different alternatives, by modifying the value of the bound T in the maximal difference model and using any population-based method to solve the corresponding, maximal difference problem. The dual-criterion MGA algorithm that follows constructs a pre-determined number of maximally different, near-optimal alternatives, by modifying the bound value T in the maximal difference model and using any population-based technique to solve the corresponding maximal difference problem. Each solution in the population comprises one set of p different alternatives. By exploiting the co-evolutionary aspects of the algorithm, the algorithm evolves each solution toward sets of dissimilar local optima within the solution domain. In this processing, each solution alternative mutually experiences the search steps of the algorithm. Solution survival depends upon both how well the solutions perform with respect to the modelled objective(s) and by how far apart they are from every other alternative in the decision space.

A straightforward process for generating alternatives solves the maximum difference model iteratively by incrementally updating the target T whenever a new alternative needs to be produced and then re-solving the resulting model [34]. This iterative approach parallels the seminal Hop, Skip, and Jump (HSJ) MGA algorithm [8] in which the alternatives are created one-by-one through an incremental adjustment of the target constraint. While this approach is straightforward, it entails a repetitive execution of the optimization algorithm [7], [12], [13]. To improve upon the stepwise HSJ approach, a concurrent MGA technique was subsequently designed based upon co-evolution ([13], [15], [17]). In a co-evolutionary approach, pre-specified stratified subpopulation ranges within an algorithm's overall population are established that collectively evolve the search toward the specified number of maximally different alternatives. Each desired solution alternative is represented by each respective subpopulation and each subpopulation undergoes the common processing operations of the procedure. The survival of solutions in each subpopulation depends simultaneously upon how well the solutions perform with respect to the modelled objective(s) and by how far away they are from all of the other alternatives. Consequently, the evolution of solutions in each subpopulation toward local optima is directly influenced by those solutions contained in all of the other subpopulations, which forces the concurrent co-evolution of each subpopulation towards good but maximally distant regions within the decision space according to the maximal difference model [7]. Co-evolution is also much more efficient than a sequential HSJ-style approach in that it exploits the inherent population-based searches to concurrently generate the entire set of maximally different solutions using only a single population [12], [17].

While concurrent approaches can exploit population-based algorithms, co-evolution can only occur within each of the stratified subpopulations. Consequently, the maximal differences between solutions in different subpopulations can only be based upon aggregate subpopulation measures. Conversely, in the following simultaneous MGA algorithm, each solution in the population contains exactly one entire set of alternatives and the maximal difference is calculated only for that particular solution (i.e. the specific alternative set contained within that solution in the population). Hence, by the evolutionary nature of the population-based search procedure, in the subsequent approach, the maximal difference is simultaneously calculated for the specific set of alternatives considered within each specific solution – and the need for concurrent subpopulation aggregation measures is avoided.

Using the data structure terminology, the steps for the dual-criterion MGA algorithm are as follows ([14], [19], [20], [21], [22], [23], [34], [35], [36]). It should be readily apparent that the stratification approach employed by this method can be easily modified for any population-based algorithm.

Initialization Step. Solve the original optimization problem to find its optimal solution, **X***. Based upon the objective value F(**X***), establish P target values. P represents the desired number of maximally different alternatives to be generated within prescribed target deviations from the **X***. Note: The value for P has to have been set a priori by the decision-maker.

Without loss of generality, it is possible to forego this step and to use the algorithm to find **X*** as part of its solution processing in the subsequent steps. However, this significantly increases the number of iterations of the computational procedure and the initial stages of the processing become devoted to finding **X*** while the other elements of each population solution are retained as essentially "computational overhead".

Step 1. Create an initial population of size K where each solution contains P equally-sized partitions. The partition size corresponds to the number of decision variables in the original optimization problem. $\mathbf{X}_{\mathbf{k}p}$ represents the p^{th} alternative, p = 1,…,P, in solution $\mathbf{Y}_\mathbf{k}$, k = 1,…,K.

Step 2. In each of the K solutions, evaluate each $\mathbf{X}_{\mathbf{kp}}$, p = 1,…,P, using the simulation module with respect to the modelled objective. Alternatives meeting their target constraint and all other problem constraints are designated as feasible, while all other alternatives are designated as infeasible. A solution can only be designated as feasible if all of the alternatives contained within it are feasible.

Step 3. Apply an appropriate elitism operator to each solution to rank order the best individuals in the population. The best solution is the feasible solution containing the most distant set of alternatives in the decision space (the distance measures are defined in Step 5).

Note: Because the best solution to date is always retained in the population throughout each iteration, at least one solution will always be feasible. A feasible solution for the first step can always consists of P repetitions of **X***.

Step 4. Stop the algorithm if the termination criteria (such as maximum number of iterations or some measure of solution convergence) are met. Otherwise, proceed to Step 5.

Step 5. For each solution $\mathbf{Y}_k$, k = 1,…, K, calculate D^1_k and D^2_k, which are the dual-criterion Max-Min and Max-Sum distance measures determined, respectively, between all of the alternatives contained within the solution.
As an illustrative example for calculating the dual-criterion distance measures, compute

$$D^1_k = \Delta^1(\mathbf{X_{ka}}, \mathbf{X_{kb}}) = \min_{a,b,q} |X_{kaq} - X_{kbq}|, \qquad a = 1,\dots,P,\ b = 1,\dots,P,\ q = 1,\dots,n, \tag{7}$$

and

$$D^2_k = \Delta^2(\mathbf{X}_{ka}, \mathbf{X}_{kb}) = \sum_{a=1 to P} \sum_{b=1 to P} \sum_{q=1\dots n} (X_{kaq} - X_{kbq})^2, \tag{8}$$

D^1_k denotes the minimum absolute distance and D^2_k represents the overall quadratic deviation between all of the alternatives contained within solution k. Alternatively, the distance functions could be calculated by some other appropriately defined function.

Step 6. This step orders the specific solutions by those solutions which contain the set of alternatives which are most distant from each other. The goal of maximal difference is to force alternatives to be as far apart as possible in the decision space from the alternatives of each of the partitions within each solution.

Let $D_k = G(D^1_k, D^2_k)$ represent the dual-criterion objective for solution k. Rank the solutions according to the distance measure D_k objective – appropriately adjusted to incorporate any constraint violation penalties for infeasible solutions.

Step 7. Apply applicable algorithmic "change operations" to each solution within the population and return to Step 2.

V. CASE STUDY OF WATER RESOURCES MANAGEMENT

As indicated throughout the previous sections, WRM decision-makers faced with situations containing numerous uncertainties often prefer to select from a set of "near best" alternatives that differ significantly from each other in terms of the system structures characterized by their decision variables. The efficacy of the population-based, dual-criterion MGA procedure will be illustrated using a WRM case taken from [24] and [25]. While this section briefly summarizes the case, more explicit details, data, and descriptions can be found in [24], [25], [37], [38], [39], [40].

Previous research ([24], [25]) examined a WRM problem for allocating water in a dry season from an unregulated reservoir to three categories of users: (i) a municipality, (ii) an industrial concern, and (iii) an agricultural sector. The industrial concern and agricultural sector were undergoing significant expansion and needed to know the quantities of water they could reasonably expect. If insufficient water was available, these entities would be forced to curtail their capital expansion plans. If the promised water was delivered, it would contribute positive net benefits to the local economy per unit of water allocated. However, if the water was not delivered, the results would reduce the net benefits to the users.

The major problems under these circumstances involved (i) how to effectively allocate water to the three user groups in order to achieve maximum net benefits under the uncertain conditions and (ii) how to incorporate the water policies in terms of allowable amounts within this planning problem with the least risk of system disruption. Included within these decisions is a determination of which one of the multiple possible pathways that the water would flow through in reaching the users. It is further possible to subdivide the various water streams with each resulting substream sent to a different user. Since cost differences from operating the facilities at different capacity levels produce economies of scale, decisions have to be made to determine how much water should be sent along each flow pathway to each user type. Therefore, any single policy option can be composed of a combination of many decisions regarding which facilities received water and what quantities of water would be sent to each user type. All of these decisions were compounded by overriding system uncertainties regarding the seasonal water flows and their likelihoods.

The WRM case considers how to effectively allocate the water to the three user groups in order to derive maximum net benefits under the elements of uncertainty and how to incorporate water policies in terms of allowable amounts within this planning problem with the least risk for causing system disruption. Since the uncertainties could be expressed collectively as interval estimates, probability distributions and uncertainty membership functions, the approach of [25] was used to show how to improve upon the earlier efforts of [24] by providing a solution for the WRM problem with a net benefit of $2.02 million.

In the region studied, the municipal, industrial, and agricultural water demands have been increasing due to population and economic growth. Because of this, it is necessary to ensure that the different water users know where they stand by providing information that is needed to make decisions for various activities and investments. For example, farmers who know there is only a small chance of receiving sufficient water in a dry season are not likely to make major investment in irrigation infrastructure. Similarly, industries are not likely to promote developments of projects that are water intensive knowing that they will have to limit their water consumption. If the promised water cannot be delivered due to insufficiency, the users will have to either obtain water from more expensive alternate sources or curtail their development plans. For example, municipal residents may have to curtail watering of lawns, industries may have to reduce production levels or increase water recycling rates, and farmers may not be able to conduct irrigation as planned. These impacts will result in increased costs or decreased benefits in relation to the regional development. It is thus desired that the available water be effectively allocated to minimize any associated penalties. Thus, the problem can be formulated as maximizing the expected value of the net system benefits. Based upon the local water management policies, a quantity of water can be pre-defined for each user. If this quantity is delivered, it will result in net benefits; however, if not delivered, the system will then be subject to penalties.

The WRM authority is responsible for allocating water to each of the municipality, the industrial concerns, and the agricultural sector. As the quantity of stream flows from the reservoir are uncertain, the problem is formulated as a stochastic programming problem. This stochastic programming model can account for the uncertainties in water availability. However, uncertainties may also exist in other parameters such as benefits, costs and water-allocation targets. In the formulation, penalties are imposed when policies that have been expressed as targets are violated. Also, within the model, any uncertain parameter A is represented by $A^{\pm}$ and its corresponding values are generated via probability distributions. To reflect all of these uncertainties, the following stochastic programming model was constructed by [25]:

$$Max\ f^{\pm} = \sum_{i=1}^{m} B_i^{\pm} W_i^{\pm} - \sum_{i=1}^{m}\sum_{j=1}^{n} p_j C_i^{\pm} S_{ij}^{\pm} \qquad (9)$$

$$\sum_{i=1}^{m}\left(W_i^{\pm} - S_{ij}^{\pm}\right) \le q_j^{\pm} \qquad \forall\, j \qquad (10)$$

$$S_{ij}^{\pm} \le W_i^{\pm} \le W_{i\max}^{\pm} \qquad \forall\, i \qquad (11)$$

$$S_{ij}^{\pm} \ge 0 \qquad \forall\, i, j \qquad (12)$$

In this formulation $f^{\pm}$ represents the net system benefit (\$/m^3) and $B_i^{\pm}$ represents the net benefit to user i per m^3 of water allocated (\$). $W_i^{\pm}$ is the fixed allocation amount (m^3) for water that is promised to user i, while $W_{i\max}^{\pm}$ is the maximum allowable amount (m^3) that can be allocated to user i. The loss to user i per m^3 of water not delivered is given by $C_i^{\pm}$, where $C_i > B_i$ (\$). $S_{ij}^{\pm}$ corresponds to the shortage of water, which is the amount (m^3) by which W_i is not met when the seasonal flow is q_j. $q_j^{\pm}$ is the amount (m^3) of seasonal flow with p_j probability of occurrence under j flow level, where p_j provides the probability (%) of occurrence of flow level j. The variable i, i = 1, 2, 3, designates the water user, where i = 1 for municipal, 2 for industrial, and 3 for agricultural. The value of j, j = 1, 2, 3, is used to delineate the flow level, where j = 1 represents low flows, 2 represents medium flows, and 3 represents high flows. Finally, m is the total number of water users and n is the total number of flow levels.

WRM planners faced with difficult and controversial choices generally prefer to select from a set of near-optimal alternatives that differ significantly from each other in terms of their system structures. In order to create these alternative planning options for the WRM system, it would be possible to place extra target constraints into the original model which would force the generation of solutions that were different from their respective, initial optimal solutions. Suppose for example that five additional planning alternative options were created through the inclusion of a technical constraint on the objective function that decreased the total system benefits of the original model from 2% up to 10% in increments of 2%. By adding these incremental target constraints to the original SO model and sequentially resolving the problem 5 times, it would be possible to create a specific number of alternative policies for WRM planning.

However, to improve upon the process of running five separate additional instances of the computationally intensive SO algorithm to generate these solutions, the population-based, dual-criterion MGA procedure described in the previous section was run only once, thereby producing the 5 additional alternatives shown in Table 1. The table shows the overall system benefits for the 5 maximally different options generated. Given the performance bounds established for the objective in each problem instance, the decision-makers can feel reassured by the stated performance for each of these options while also being aware that the perspectives provided by the set of dissimilar decision variable structures are as different from each other as is feasibly possible. Hence, if there are stakeholders with incompatible standpoints holding diametrically opposing viewpoints, the policy-makers can perform an assessment of these different options without being myopically constrained by a single overriding perspective based solely upon the objective value.

Maximally Different Solutions	WRM System Benefits ($ Millions)
Best Solution Overall	2.02
Best Solution Within 2%	1.98
Best Solution Within 4%	1.96
Best Solution Within 6%	1.92
Best Solution Within 8%	1.88
Best Solution Within 10%	1.81

Table 1 System Benefits ($ Millions) for 6 Maximally Different Alternatives

The computational example highlights several important aspects with respect to the MGA technique: (i) Population-based algorithms can be effectively employed as the underlying optimization search procedure for SO routines; (ii) Population-based solution searches can simultaneously generate more good alternatives than planners would be able to create using other MGA approaches; (iii) By the design of the MGA algorithm, the alternatives generated are good for planning purposes since all of their structures are guaranteed to be as mutually and maximally different from each other as possible (i.e. these differences are not just simply different from the overall optimal solution as in an HSJ-style approach to MGA); (iv) The approach is very computationally efficient since it need only be run once to generate its entire set of multiple, good solution alternatives (i.e. to generate n maximally different solution alternatives, the MGA algorithm would need to be run exactly the same number of times that the FA would need to be run for function optimization purposes alone – namely once – irrespective of the value of n); and, (v) The best overall solutions produced by the MGA procedure will be identical to the best overall solutions that would be produced for function optimization purposes alone.

VI. CONCLUSIONS

WRM decision-making problems contain multifaceted performance requirements which inevitably include complicated, incongruent performance objectives and unquantifiable modelling features. These problems often possess incompatible design specifications which are difficult – if not impossible – to capture when the supporting decision models are formulated. Consequently, there are unmodelled problem components, generally not apparent during model construction, that can significantly influence the acceptability of any model's solutions. These competing and ambiguous components force WRM decision-makers to incorporate many conflicting requirements into their decision process prior to settling upon a final solution.

This paper has applied a population-based, dual-criterion MGA procedure to WRM. This computationally efficient MGA approach establishes how population-based algorithms can simultaneously construct entire sets of close-to-optimal, maximally different alternatives by exploiting the evolutionary characteristics of population-based solution algorithms. In this MGA role, the dual-criterion objective can efficiently generate the requisite set of dissimilar alternatives, with each generated solution providing an entirely different perspective to the problem. The max-sum objective criteria ensures that the distances between the alternatives created by this approach are good in general, while the max-min criteria ensures that the distances between the alternatives are good in the worst case. The absolute function has been considered, since its value provides a meaningful, physical interpretation to its measure of distance. Since population-based procedures can be applied to a wide range of problem types, the practicality of this dual-criterion MGA approach can be extended to wide array of "real world" environmental applications. Such extensions will be explored in future computational studies.

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