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ECONOMIC OPTIMIZATION OF RIVER MANAGEMENT USING GENETIC ALGORITHMS

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ABSTRACT

In this research, we investigated the potential of a genetic algorithm based technique to optimize the operation of a complex water resources problem. Current approaches to this problem represent a tradeoff between model accuracy and optimization capability. Both a dynamic programming and genetic algorithm approach were applied to a simple water resources exercise. As the exercise grew in complexity, the calculation time for the dynamic programming approach increased rapidly. The genetic algorithm approach experienced a much smaller increase in calculation time. The genetic algorithm approach was then applied to the problem of optimizing the operation of a complex simulation model of the Rio Grande Project (RGP) in southern New Mexico. Although it did not model the behavior of the RGP with complete accuracy, the simulation model was representative of the complexity required to do so. The genetic algorithm was able to guide the search to better operating strategies, demonstrating the potential of genetic algorithms to optimize the operation of realistic system models when they are available.

Keywords: genetic algorithm, water resources, management, optimization

INTRODUCTION

Throughout New Mexico, water availability is one of the major constraints to economic development. In most areas, rivers are fully allocated, or, as on the Pecos River, over allocated. Water management has been largely based on staff experience of the US Bureau of Reclamation (USBR) and the New Mexico State Engineer Office (SEO). While their experience has been adequate in the past, increasing pressure on water resources for expanding urban areas, irrigation, recreation, hydroelectric production, and interstate agreements is rapidly changing the system requirements and creating economic and legal battles between water users. Water resources planners and managers, including federal and state agency and irrigation district managers, must pursue policies to utilize efficiently a limited water supply. To do so, they need management tools that can help identify strategies that maximize the economic benefits of river operation.

Optimizing economic benefits of river operation is a classic and persistent problem in water resource engineering and management. So many options exist for managing a river/reservoir system that a human operator cannot consider each possibility thoroughly. Attempts to use computers and mathematical programming techniques to find optimal management strategies that maximize economic benefits from water resources have been only marginally successful because of the complexity and wide range of possible operating policies. If a truly representative computer model of a river system is used for optimization, the number of options that must be considered is too large to be handled with traditional techniques. If the river model is simplified enough to be manageable, the model loses important representative characteristics. Therefore, most rivers are managed following protocols and policies developed through experience. While these methods may currently be adequate, they often are not optimum and do not adapt quickly to changing physical and economic conditions. As water demands increase and outstrip available resources, operating at non-optimal conditions becomes exceedingly expensive, making the development of adequate management tools even more crucial. This is a problem on nearly all major rivers in New Mexico and the entire United States.

Developing management tools for optimization of economic benefits from river basin operation is a continuing need in water resources management. Searching for optimal management strategies is complicated but crucial. River basin systems are increasingly multipurpose, supplying water for irrigation, hydropower generation, recreational, and municipal and industrial users. In addition, water quality improvement and fish and wildlife enhancement are gaining increasing importance in management decisions. In some systems, the requirements of navigation and flood control must also be considered. Constraints on the operation of the system are quite complicated. Typical constraints include maximum and minimum storage, maximum and minimum releases, and equipment and facility limitations for each reservoir of the system. Additional constraints include obligations created by the various users of the system. The relationship between system response and management decisions is quite complicated. In addition, both inflow to the system and users' demands vary seasonally and with changing hydrological conditions. Identifying management strategies that optimize the benefits provided to users of multi reservoir river basin systems, subject to operating constraints, is difficult. Developing reliable tools to aid in this task is an ongoing research effort in the field of operations research and water resources engineering.

The immediate aim of this research was to investigate the potential of genetic algorithms to provide a management tool for improving the economic performance of river basin management. Genetic algorithms have been effective in a broad range of optimization problems and may well provide the key to computer-based river management. The Rio

Grande Project (RGP) in southern New Mexico was selected as a proving ground for a river management optimization technique based on a genetic algorithm. Demands on this project include a wide range of local water uses as well as compliance with interstate and international agreements. In addition to being a multipurpose system, the RGP is a multi-facility system with reservoirs at Elephant Butte and Caballo. Water resources engineers have previously applied operations research and simulation techniques to this type of problem with limited success. This research was undertaken to determine the suitability of genetic algorithms for such problems.

OBJECTIVE

The project's overall goal was to investigate the use of a genetic algorithm to optimize the economic benefits of a complex river system management model. Such a river management model would be capable of portraying both the physical response to and economic benefits of particular operating strategies. We developed a model whose estimates of physical and economic response represented those of the RGP system. To develop this model, we made use of available data and the expertise of the current system operators, the U.S. Bureau of Reclamation, and previous research efforts. Appropriate hydraulic and economic components of the RIOFISH model developed by Cole et al. (1990) also were incorporated. With these ingredients, we were able to formulate the RGP management problem to a level of complexity sufficient to demonstrate the potential of a management tool.

Our model was representative, but not perfectly accurate in simulating the response of the RGP. It was beyond the scope of this research to develop a completely accurate model of the RGP. We focused on developing a genetic algorithm to find optimal operating policies for a water resources system model of realistic complexity. A truly accurate model of the physical response of the RGP and/or its economic behavior does not currently exist. Our model retained much of the complexity of the RGP and was sufficient for our purposes. Our results, however, should be interpreted in this light.

This investigation demonstrates the suitability of using genetic algorithms to find operating strategies for complex system models. It appears that if an accurate system model of the RGP were available, a genetic algorithm could determine good operating policies using the model. Developing such a model is beyond the scope of this research. Our results should be used to evaluate the performance of a genetic algorithm in finding optimal operating strategies for a complex water resources problem. Because of our system model's limitations, our results should not be used to find better operating strategies for the RGP.

THEORETICAL BACKGROUND

CURRENT MANAGEMENT TOOLS

For over 20 years, engineers have been developing optimization techniques for the management of complex water resources systems. These efforts have been documented by Wurbs (1993), Simonovic (1992), Yeh (1985), and others. In his review of state-of-the-art methods for river and reservoir management, William Yeh (1985) discusses four broad classifications of optimization techniques. The first three, linear, dynamic, and nonlinear programming, are based on mathematical programming techniques. Each of these approaches requires a very specific formulation of the reservoir management problem in order to apply the particular technique. All three approaches are proven optimizing techniques. In practice, however, successful application has been limited to relatively simple systems; either multipurpose, single facility or single purpose and multi facility systems. When applied to multipurpose, multi facility systems, these approaches are forced to operate on a simplified model of the system to avoid prohibitively large computing times. These simplifications have greatly devalued the results attainable with these techniques.

The final method for optimizing reservoir management that Yeh reviewed was the use of computer simulations to model the behavior or reservoir systems. These simulations provide a means to predict accurately the response of the system to specified inputs, including management decisions. In general, they model reservoir systems to a much greater level of detail than mathematical programming techniques. Unlike mathematical programming techniques, they do not directly optimize operation of the system. They have been used, however, to evaluate the merits of competing management alternatives. Recently, researchers have attempted to incorporate optimization methods within simulation models. This requires a means for selecting competing management strategies that can then be evaluated with the simulation model. Because of the greater detail retained by simulations, the number of possible strategies for these models is much greater than those for more simplified mathematical programming models. In addition, the problem is not formulated in a manner that readily allows the identification of infeasible strategies. Heuristic means of determining strategies have not proven capable of adequately searching the possible strategies. Mathematical methods of selecting strategies, such as gradient decent methods and mapping of the simulation response surfaces, have been unattractive because of huge computational requirements. Water resources engineers are still looking for an optimization technique that can adequately search for optimal management strategies while retaining the level of detail of computer simulations.

An example of the shortfall of traditional methods in optimizing river management is given by the work of Salem and Jacob (1971) on the Roswell Basin of the Pecos River in New Mexico. The researchers attempted to find optimal operating strategies for a coupled system of surface waters and two aquifers in the region. They took a traditional approach, using dynamic programming to find solutions. To do this expediently, a simplified objective function and model of the system was required. These simplifications limited the solutions usefulness. This has been the principal weakness of traditional approaches to river management problems.

At present, completely satisfactory tools for river basin management have not been developed. Currently available management tools for river basin operation represent a trade-off between model accuracy and optimization capability. T.A. Austin (1986) found that this trade-off limited the usefulness of these management tools. He surveyed water resource engineers from state agencies and consulting firms regarding their use of computer models in planning, design, and operation of water resources systems. These engineers felt that one of the largest obstacles limiting the use of such management tools in their organizations was their inability to represent the "real world" situations they encountered. Considering this concern, it was not surprising that the survey also found simulation models were much more widely used than optimization models. Simulation models were considered to be more useful because they more accurately model water resource systems. These models could be used to predict accurately the response of the system to individual management policies. They do not, however, provide a means to find optimal management policies. As a result, the management of most rivers is still very dependent on protocols and policies developed through experience.

GENETIC ALGORITHMS

Genetic algorithms in conjunction with accurate simulation models appear to have the potential to provide water resource managers with management tools that have both optimization capabilities and model accuracy. Genetic algorithms are a class of search techniques quite different from conventional optimization methods. Based upon their success in solving problems in other fields, genetic algorithms may help managers find more efficient strategies to utilize water resources.

Because of their recent development, genetic algorithms are not as well known as more traditional optimization techniques. They are described as "genetic" algorithms because the processes of natural selection are analogous to the search procedures they employ. As pointed out by DeJong (1988), genetic algorithms are truly a class of search techniques. Within a fairly general framework, there are many possible variations. Various genetic algorithms will differ by the manner in which they implement each of the basic elements. Davis and Streenstrup (1987) described the basic elements necessary to solve a specific problem with a genetic algorithm. Their description seems quite useful in differentiating between the various possible implementations of genetic algorithms. They list five components of a genetic algorithm:

A. **A chromosomal representation of problem solutions:** This is a string coding of the natural parameter set of the problem. In most work performed with genetic algorithms, binary strings (base two strings of 0's and 1's) have been utilized. Other representations have sometimes been chosen but have not been studied as extensively.

B. **A method for creating an initial generation of problem solutions:** Once a representation scheme has been selected, a method of producing an initial "generation" or set of strings is necessary. Instead of searching from one single point to another in a solution space, a genetic algorithm searches from one set of points to another. This makes genetic algorithm guided search more global in nature. To begin the search, a genetic algorithm must be supplied with an initial generation of strings. Initial generations filled with randomly generated strings provide a thorough search of the range of possible solutions and have been used in many applications.

C. **An evaluation function to determine the fitness of each string:** The evaluation function plays the part of the objective function used in more traditional optimization techniques. This function is used to compare the individual strings of the population in terms of their worth or fitness.

D. **Genetic operators that produce the next generation of strings from the present generation:** Although many such operators have been developed and studied, reproduction and crossover are two of the most basic. Together, these operators give genetic algorithms much of their power. Reproduction selects the highest fitness strings of the current generation to be used to create members of the next. Crossover exchanges information between these higher fitness strings. Reproduction and crossover act to focus the search in the region near high benefit strings.

E. **Genetic algorithm parameter values:** These values determine the nature and behavior of the genetic algorithm search. These values include the population size (the number of strings included in a generation) and rate at which genetic operators are applied.

The following example is intended to illustrate how a genetic algorithm could be used to optimize a simple function. Although the function has an obvious analytical solution, this example demonstrates how the components discussed above are applied in a simple genetic algorithm. The algorithm will be used to maximize the following function:

$$f(i) = -\frac{1}{4}i^2 + 8i + 1$$

where i is an integer on the interval from 0 to 31. This function, which has a maximum value of 65 when i is 16, is shown in Figure 1.

The genetic algorithm components described by Davis and Streenstrup will be applied in the following way:

A. The 32 possible values of i will be represented as binary strings of length five.

B. The initial generation will be filled with strings generated randomly.

C. The quadratic equation to be maximized will be the 'fitness' function.

D. Our genetic operators will be reproduction and crossover only.

E. The number of strings in each generation will be set to four.

The genetic algorithm proceeds as shown in the flow chart in Figure 2. This figure is divided into ten blocks, labeled 0 through 9. The values of i for the initial generation are chosen at random to be 18, 4, 24, and 31. As shown in Block 1, these values are encoded as binary numbers which become the strings of the initial generation. The fitness of these strings is calculated with the fitness function in Block 2. The initial generation has a total fitness of 150.75 and an average fitness of 37.69. The best string of this generation has a value of 64. After evaluation is complete, the algorithm checks if the termination criteria are fulfilled. In this case, the condition is completion of a certain number of generations.

If the required number of generations have not been completed, the genetic algorithm adjusts the generation count (Block 3) and produces another generation by applying the reproduction and crossover operators. The reproduction operator (Block 4) is applied first to select strings from the current generation that will be used to create the next generation of strings. This operator is preferential to strings with higher fitness, making a string's

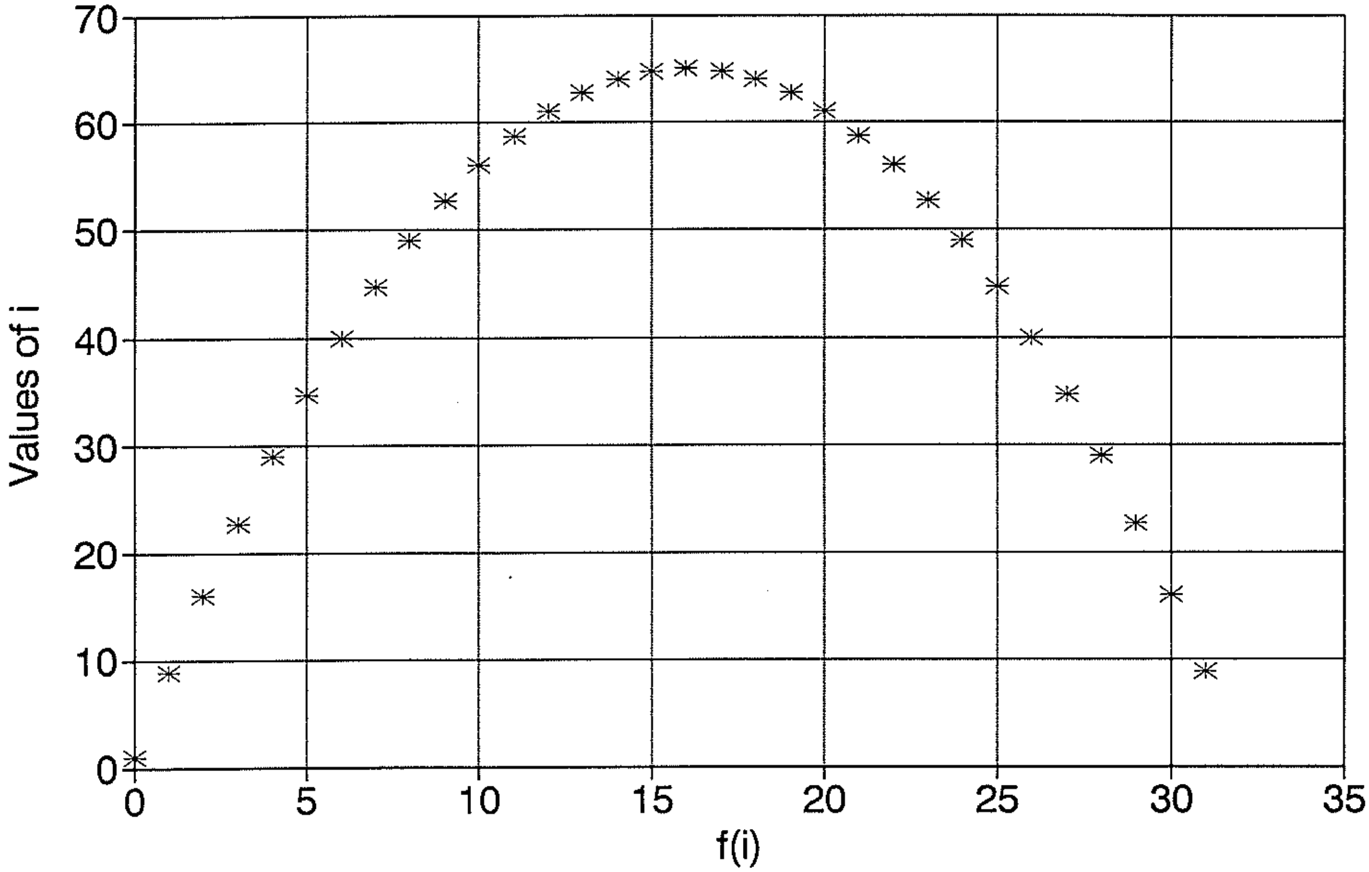

Fig. 1 Objective Function for Example Problem

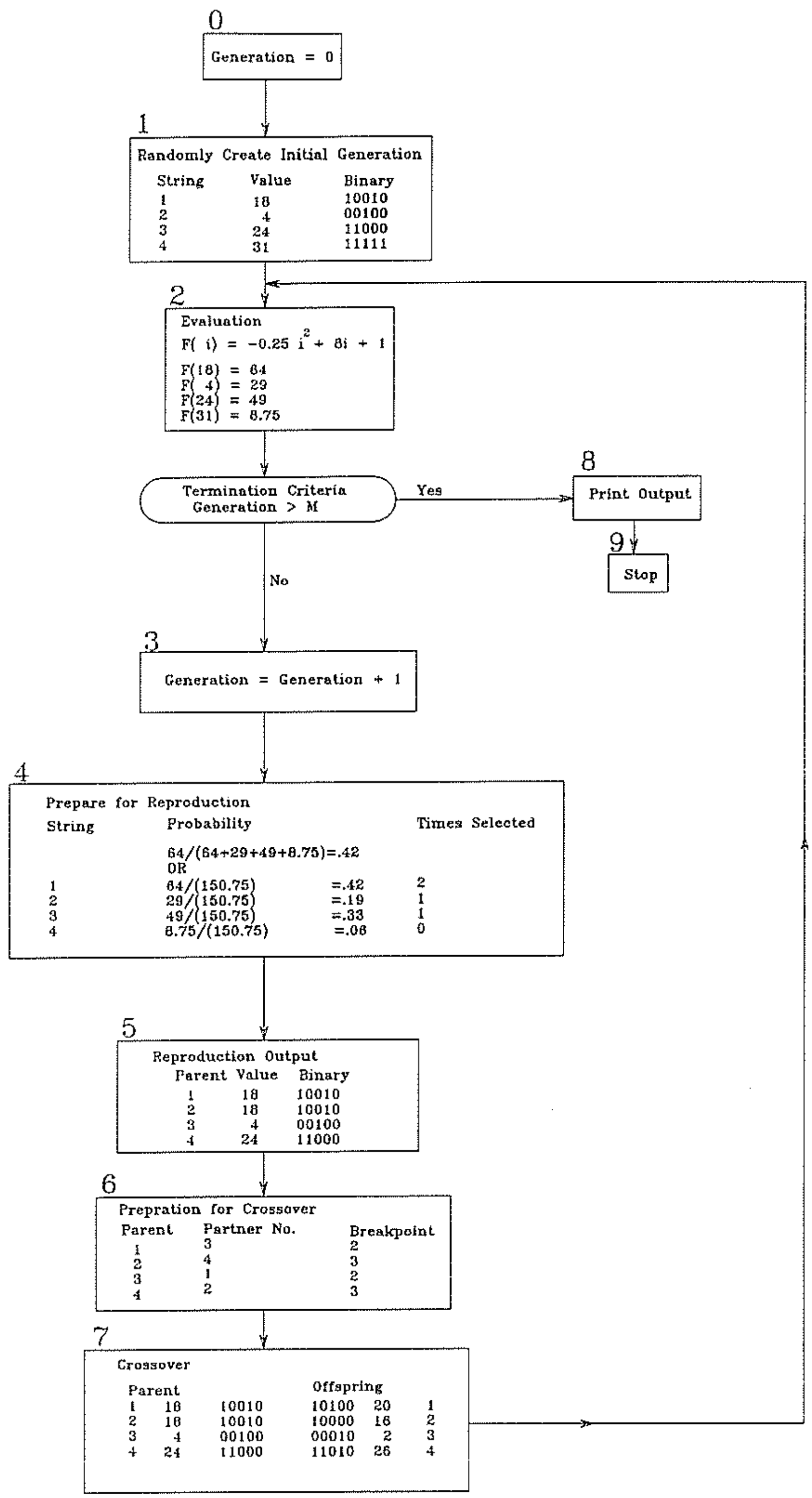

Fig. 2 Flow Chart of Simple Genetic Algorithm

Search Procedure

probability of being selected equal to the ratio of its fitness to the total fitness of the entire population. In this way, above average fitness strings are more likely to be selected. The selection probability for the first string is 0.42 (42%), meaning that if one hundred selections were made, we would expect this string to be chosen 42 times. Using these probabilities, the reproduction operator makes four independent selections from the current generation. Because of it's high probability, it is not surprising that the first string is selected twice. Strings 2 and 3 are also chosen. These strings, shown in the Block 5, become the "parent" strings that will be used by the crossover operator.

The crossover operator is applied to the parent strings in order to develop new strings for the next generation. Parent strings supplied by the reproduction operator are paired off at random. As shown in Block 6, parent 1 is paired with parent 3 and parent 4 is paired with parent 2. A specific location between bits of the parent strings or "breakpoint" is chosen at random for each pair of parents. There are four possible breakpoints for strings of five bits. Both parent strings are broken at this location and the portion of string beyond this position is exchanged with its partner. This procedure creates new "offspring" strings (Block 7). Before crossover, the parent strings (with their breakpoints shown by the "¦" character) look like this:

```
          Parent 1       1 0¦0 1 0        Parent 2     1 0 0¦1 0

          Parent 3       0 0¦1 0 0        Parent 4     1 1 0¦0 0

                           ^ ^ ^ ^                       ^ ^ ^ ^

  Possible Breakpoints     1 2 3 4                       1 2 3 4
```

After crossover, the offspring strings are:

Offspring 1	1 0¦1 0 0	Offspring 2	1 0 0¦0 0
Offspring 3	0 0¦0 1 0	Offspring 4	1 1 0¦1 0

These offspring strings, corresponding to values for *i* of 20, 16, 2, and 26, become the strings of the next generation. These strings are returned to Block 2 for evaluation. The new generation is found to have improved performance with a total fitness of 198 and an average value of 49.5. The best string has a value of 65. Continuing from this point, more iterations of the search procedure could be performed. Future generations would continue to show increased performance as their strings begin to converge to the optimal value of 16. For this relatively easy problem, the simple genetic algorithm is working.

Although the test function is a very easy one, we can still make some observations about the genetic algorithm used in this example. As promised, the reproduction operator of this algorithm has preferentially selected strings. Similarly, the crossover operator has generated new strings for the next generation. By comparing the sum, average, and maximum string fitness for the initial population and next generation, we see that fitness has improved.

Table 1 compares genetic algorithms with the most popular optimization techniques that have previously been applied to the problem of optimizing river basin management. Linear programming has been a popular technique because of ease of problem formulation and its ability to find truly global optimum points. Unfortunately, the problem of optimizing river basin management is nonlinear because of the nonlinear relationship between reservoir storage, surface area, and elevation. Benefit functions and operating constraints also are often nonlinear. Use of linear programming for these problems requires that the problem be "linearized." This results in simplifications that reduce the value of optimization results.

Table 1. Comparison of Optimization Techniques

Optimizing Technique	Applicable Problems	Advantages	Disadvantages
Linear Programming	Linear	Easy Problem Formulation, Global Optimum	Nonlinear Problems Must be Linearized and Simplified
Dynamic Programming	Nonlinear	Handles Nonlinear Problems	Intractable for Many Dimensions
Nonlinear Programming	Nonlinear, Continuous	Handles Nonlinear Problems	Computation Intensive, Trapped by Local Optimum
Genetic Algorithm	Nonlinear	Handles Nonlinear Problems, Derivatives Unnecessary, Global Search	Not Competitive on Small Problems

Dynamic programming is capable of handling nonlinear problems. However, as the number of decision variables increases for complex problems, this approach becomes intractable. This so called "Curse of Dimensionality" has limited dynamic programming to optimizing operation of simplified, low dimension river basin management problems.

Nonlinear programming techniques, such as gradient descent methods, are also capable of handling nonlinear problems. Use of these techniques has been limited because they are computationally intensive and have slow rates of convergence. These techniques also require the calculation of derivatives for their search procedure, limiting their use to problems that are continuous.

Since their development in the late 1960s, genetic algorithms have been proven effective in searching large, complex solution spaces. They are capable of solving nonlinear problems. Because they do not require derivative information to direct their search, they are not limited to problems that are continuous. Instead of progressing from point to point, like other techniques, genetic algorithms search from a set of problem solutions to another. This feature allows them to escape local optimum, making their search more global in nature. Because they require numerous evaluations of the objective function, they are not competitive with other techniques for simple problems. However, when applied to complex problems of increasing dimension, the computational requirements for genetic algorithms do not increase as quickly as those for other techniques. The search performance of genetic algorithms makes them especially suited for problems that are particularly difficult for other techniques.

Researchers have been applying genetic algorithms to an ever increasing realm of problems. Of particular interest has been the work of David E. Goldberg, a civil engineer. Goldberg (1987) has applied genetic algorithms to such varied tasks as designing trusses for structures and controlling the motion of an inertial object on a frictionless plane. His work to optimize the operation of a natural gas pipeline is similar to the problem of river management. For a simulated pipeline, Goldberg's genetic algorithm provided results similar to those obtained by more traditional techniques such as dynamic and integer programming. However, the genetic algorithm also was able to consider larger, more complex problems than had previously been considered by the other techniques. Goldberg used a genetic algorithm to find rules for the optimal operation of the pipeline subject to consumer demands, weather conditions, and leaks that varied during operation. Although this system had over one trillion possible management strategies, the genetic algorithm was able to find very near-optimal strategies after evaluating less than 3,500 strategies. He concluded that genetic algorithms are ready for application to even more difficult optimization problems in engineering.

METHODOLOGY

To evaluate the effectiveness of a genetic algorithm to guide the search for optimal solutions to complex water resources problems, we undertook two efforts. In the first, a simple water resources exercise was formulated to compare the performance of dynamic programming and genetic algorithm guided search. The exercise was formulated to allow increasing complexity. The behavior of each technique as the exercise increased in complexity was compared. The second effort was the primary focus of this research. In this effort, a genetic algorithm was applied to a computer simulation model based on the physical and economic behavior of the RGP. Although not completely accurate in modeling the RGP, this model represented a level of complexity beyond that successfully optimized with conventional techniques.

DESCRIPTION OF DP VERSUS GA EXERCISE

This exercise was a preliminary investigation to determine the strengths and weaknesses of using genetic algorithms as a water resources management tool. As described by Fahmy, et al (1994), a comparison between genetic algorithms and dynamic programming was conducted on a small test exercise. Dynamic programming is a flexible optimization technique that applies to "problems requiring a sequence of interrelated decisions" (Dreyfus and Law, 1977). It takes a whole problem and solves it by determining the best solution for each smaller, manageable subproblem. These solutions are interrelated in that they build upon one another to create the best solution for the whole problem. In this exercise we used a small, two reservoir water supply system where the reservoirs had equal capacity. The amount of water that entered the reservoir each period was fixed and known. We assumed that all the water entered the reservoirs at the beginning of each time period. If the reservoirs were full, all remaining inflow water was lost through the spillway. Water was required to remain in the reservoirs for one time period for purification; therefore, it was not available for use until the next time period. Water drawn from one reservoir was free while water drawn from the alternate reservoir cost one dollar per gallon. If no water was available from either source, a shortage cost of ten dollars per gallon was incurred.

For this exercise, we determined the lowest cost of meeting water demands using genetic algorithms and dynamic programming techniques. We systematically increased the capacity of each reservoir and the number of time periods in the exercise, establishing solutions for each scenario. Given the data, we determined how much water should be drawn from each water source at each time period to minimize cost over the planning horizon (all time periods) as a function of the reservoir's initial volume of water. Water drawn from each reservoir was considered discrete at intervals of (1×10^5) cubic meters. Water demands for each time period ($n = 1,2, \ldots ,N$) were set equal to ($n \times 10^5$) cubic meters. Initial conditions were established as one-third of the water sources capacities. Water inflows to the reservoir and alternate reservoir were equal to the square root of ($0.9\, n \times 10^5$) cubic meters.

We increased the complexity of the exercise by increasing the number of stages and number of states within each stage. The maximum number of states at all stages was used to indicate the exercise complexity. The optimum (for both dynamic programming and genetic algorithms) or near optimum (for genetic algorithms) sequences of decisions for each of these scenarios were determined and computer running times were recorded for each technique. Recorded computer running time included actual computation and data handling. Although the times were not limited to computation time, they are an indicator of the speed of each algorithm.

CASE STUDY WITH MODEL REPRESENTATIVE OF THE RGP

The primary focus of this research was to investigate the potential of genetic algorithms to provide better management tools for water resources engineers. The management tool we developed employed a genetic algorithm to optimize the operation of a simulation model for greatest economic benefit. The management tool was a package consisting of two components as shown in Figure 3. In this package, the simulation model/economic benefits estimator represented a "stand alone" component. That is, it could be usefully operated individually without the genetic algorithm. For example, a water resources manager could use the simulation model of the RGP to predict the system's response and the economic benefits generated by a specific operating policy. The genetic algorithm was used to generate policies which were evaluated by the computer model. Evaluation results were returned to the genetic algorithm and used to direct the search for new strategies.

Development of this management tool was accomplished in two phases. First, we developed a simulation model and economic benefits estimator representative of the RGP. A truly accurate model of RGP system behavior and economics does not currently exist. Development of such a model was beyond the scope of this research. Our model was not an accurate simulation of the RGP, but retained much of the system's complexity. It was adequate for the primary purpose of this research: investigating the potential of the application of genetic algorithms to complex water resources problems.

Description of RGP System

The Rio Grande Project (RGP) in southern New Mexico is an ideal proving ground for developing management tools for river management optimization. A detailed record of historical operational data is available for this system. The RGP is representative of multi

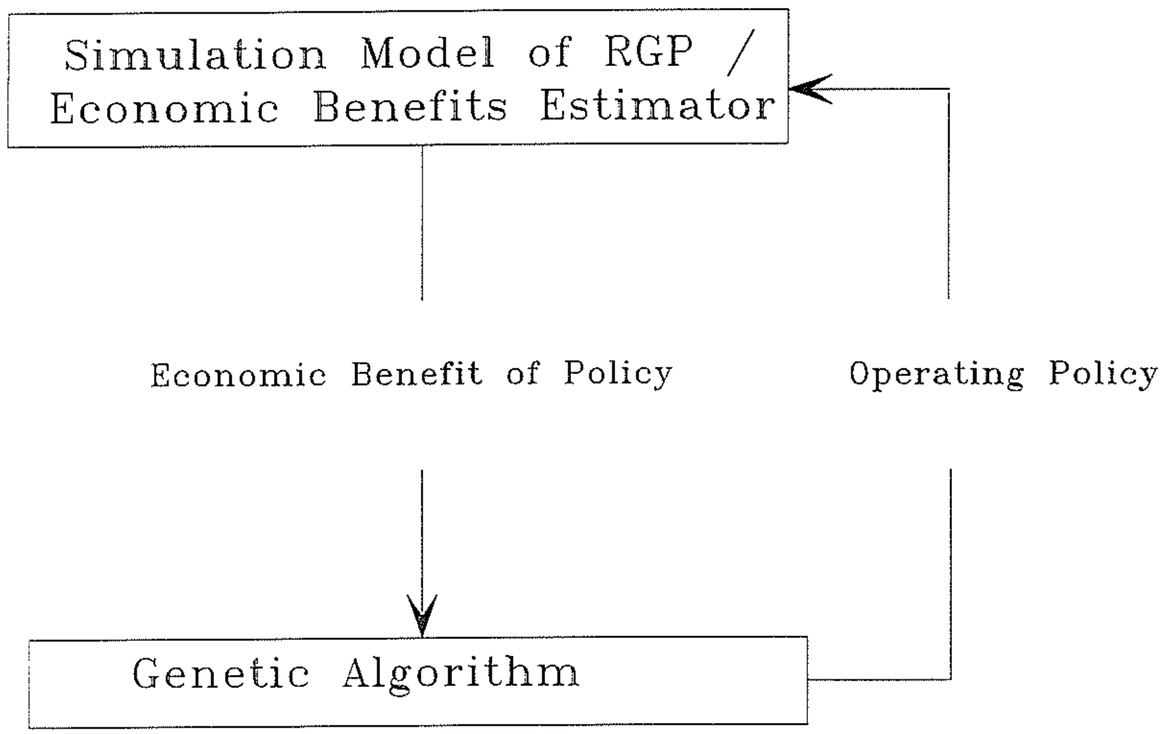

Fig. 3 Major Components of Management Tool

reservoir river systems with multiple water demands. This system includes two reservoirs, Elephant Butte and Caballo. Competing demands include hydroelectric production, agricultural, municipal and industrial, and recreational demands. The system's operation is constrained by required compliance to interstate and international treaties. These factors increase the number and complexity of operating policies. As a result, optimization of management policies for even this small portion of the Rio Grande becomes difficult for conventional methods.

The New Mexico portion of the RGP includes the following major components (also shown in Figure 4):

A. Elephant Butte Reservoir, located on the Rio Grande in southern New Mexico, is the largest body of surface water in the state. It has a storage capacity of about 2 million acre-feet, and is used for storage of Rio Grande water, production of hydroelectric power, and recreation.

B. Caballo Reservoir is located just south of Elephant Butte Reservoir and has a capacity of about 0.3 million acre-feet. It is used as a regulatory reservoir. Releases from Elephant Butte could be scheduled for hydroelectric production and the water retained in Caballo until needed for irrigation. Releases from Caballo are scheduled by orders from the irrigation districts. Its operation is, therefore, seasonal. While it was originally intended to be operated for regulation, recreational use of the reservoir has recently caused modifications to the operating protocol.

C. Elephant Butte Irrigation District (EBID) is the first irrigation district below Caballo. It services about 94,000 acres of irrigated land from three diversion points on the Rio Grande: Percha, Leasburg, and Mesilla Dams.

D. El Paso County Water Improvement District #1 (EPCWID#1) is immediately below

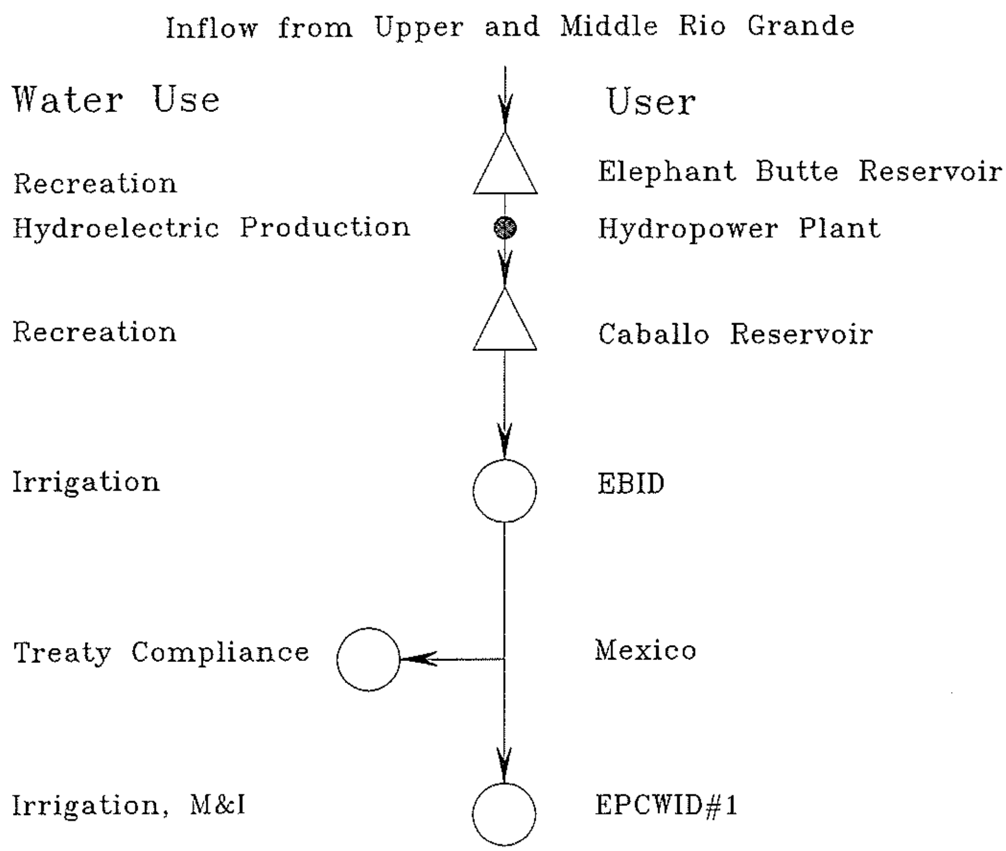

Fig. 4 Major Components of Rio Grande Project

EBID on the Rio Grande. It contains about 69,000 acres of water righted land, though typically only about 40,000 acres are irrigated. The system receives water from two diversions on the river as well as from canals originating in EBID. EPCWID#1's largest customer in terms of water use is the City of El Paso, which supplements groundwater with surface water for municipal and industrial usage.

E. Mexico, under a treaty with the United States, has a right to 60,000 acre-feet in a full allocation water year. In short water years, this is reduced proportionally to the actual allocation.

The main system of the RGP is currently operated by the US Bureau of Reclamation. Each year, based on predicted inflows and carry-over storage from the previous year (Kirby 1991), the USBR allocates water for the year to the irrigation districts. A full allocation is 954,720 acre-feet per year, though the actual allocation is generally less. Mexico is entitled to 60,000 acre-feet per year under a full allocation. EBID is entitled to 57 per cent of the remaining allocation, and EPCWID#1 is entitled to 43 per cent. The users' actual allocations are reduced proportionally in water-short years. The USBR occasionally increases the allotment during the year if inflows allow.

The RGP is a multi use system. These uses and the impact they have on operation include:

A. Hydroelectric production: Releases of water from Elephant Butte are primarily scheduled for irrigation but also are used for hydroelectric production.

B. Recreation: Income due to recreation at Elephant Butte and Caballo reservoirs can be related to reservoir storage volumes as described in Cole et al. (1990).

C. Irrigation: Irrigation water is supplied to EBID and EPCWID#1 which then apportion water to their farmers.

D. Municipal and Industrial: The City of El Paso is a major water user on EPCWID#1 and the only significant municipal user on the system. The City frequently purchases water from farmers. The price they pay varies dramatically from year to year.

E. Treaty Compliance: In full allocation years Mexico receives a 60,000 acre-feet allotment and proportionally less in years when allocations are reduced.

Throughout the year, the irrigation districts receive orders from their users. The irrigation districts consolidate these orders and request deliveries from the USBR. Releases from the reservoirs are scheduled by the USBR to meet the delivery requests at diversion points along the river. Requests for deliveries from the irrigation districts are honored until they use up their total yearly allotment.

Description of RGP Simulation Model

Our model of the Rio Grande Project, as shown in Figure 5, consists of two main reservoirs (Elephant Butte and Caballo Reservoirs), four diversion dams (Percha, Leasburg, Mesilla, and American dams), and interconnecting reaches. Historical data from 1990 were used to develop this model. Sources of data included Borland et al (1991 and 1992), IBWC (1989 and 1990), and USBR (1988 and 1991). The model makes use of 52 one-week time steps to model one year of system operation. Operating strategies for the model consist of a set of 105 operating variables. The first of these variables was the agricultural water allotment for the year in units of feet of water per water-righted acre. Values from 0 to 4 feet were considered. The remaining variables were the weekly releases from Elephant Butte and Caballo reservoirs for the year. Values for releases were limited to between 0 and 3200 cfs.

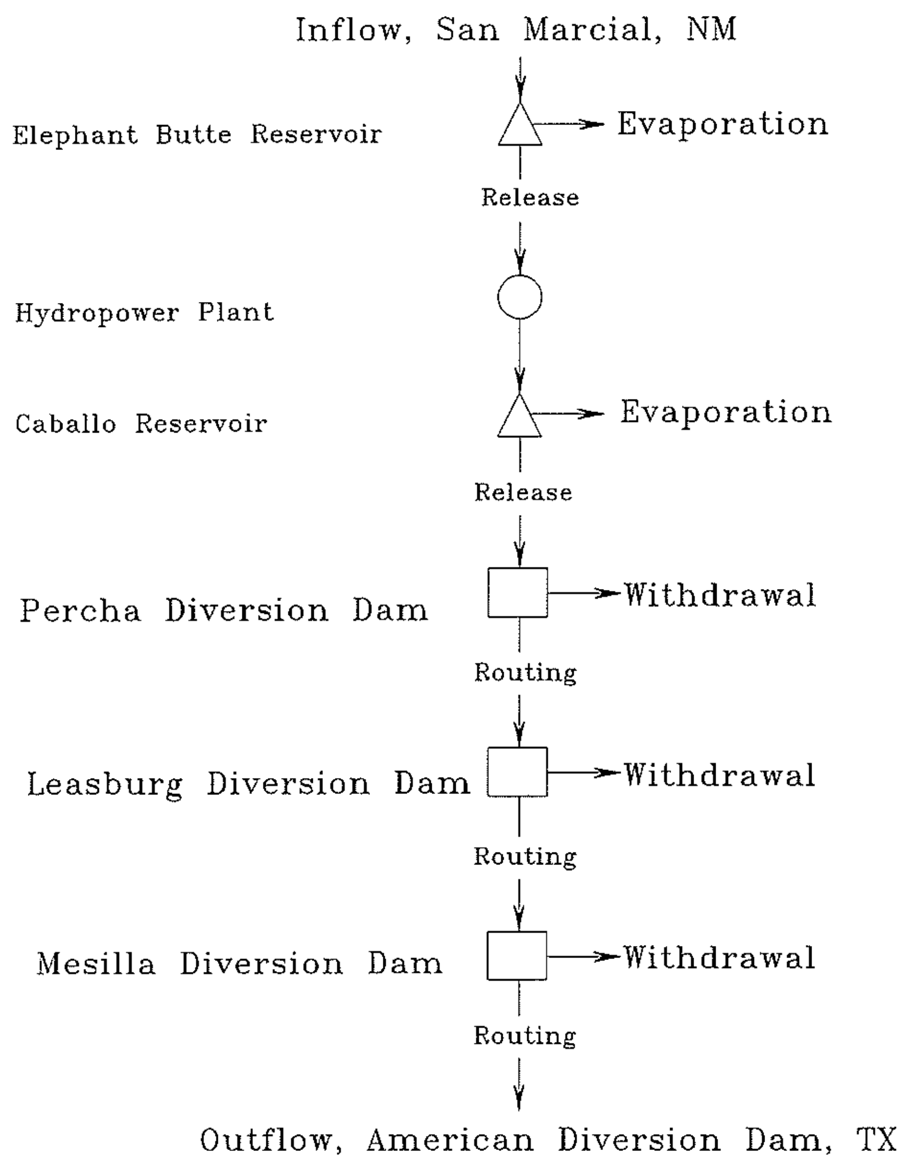

Fig. 5 Layout of Model of RGP System

Hydraulic Modeling of the RGP System

Inflow to the system occurs above Elephant Butte Reservoir at San Marcial, New Mexico. The USGS maintains a gauging station on the Rio Grande at this location and provides daily flow data for the river. Historical inflow data for 1990 was used to generate weekly flow data for inflow to the system. Data are shown in Figure 6.

A simple mass flow equation was used to model the behavior of the two main reservoirs in the RGP system. This model can be expressed by the following equation:

$$Volume_{i+1} = Volume_i + 13.8843 * Inflow - 13.8843 * Release - Evaporation$$

where $Volume_{i+1}$ is the reservoir volume for the current week in acre-feet, $Volume_i$ is the reservoir volume from the previous week in acre-feet, *Inflow* is the rate of inflow to the reservoir for the week in cfs, *Release* is the release rate from the reservoir for the week in cfs, *13.8843* is a factor to convert weekly flow rate in cfs to volume of flow for the week in acre-feet, and *Evaporation* is the weekly evaporation from the surface of the reservoir in acre-feet. The historically recorded flow at San Marcial was used as the inflow for Elephant Butte Reservoir. Releases from Elephant Butte were used as the inflow for Caballo Reservoir.

For each reservoir, equations relating water surface elevation to storage volume were developed. These were of the form:

$$Elev = A * Volume^{B} + C$$

where *Elev* is the elevation of the water surface in feet above sea level, *A*, *B*, and *C* are coefficients, and *Volume* is the storage volume of the reservoir in acre-feet. Coefficients

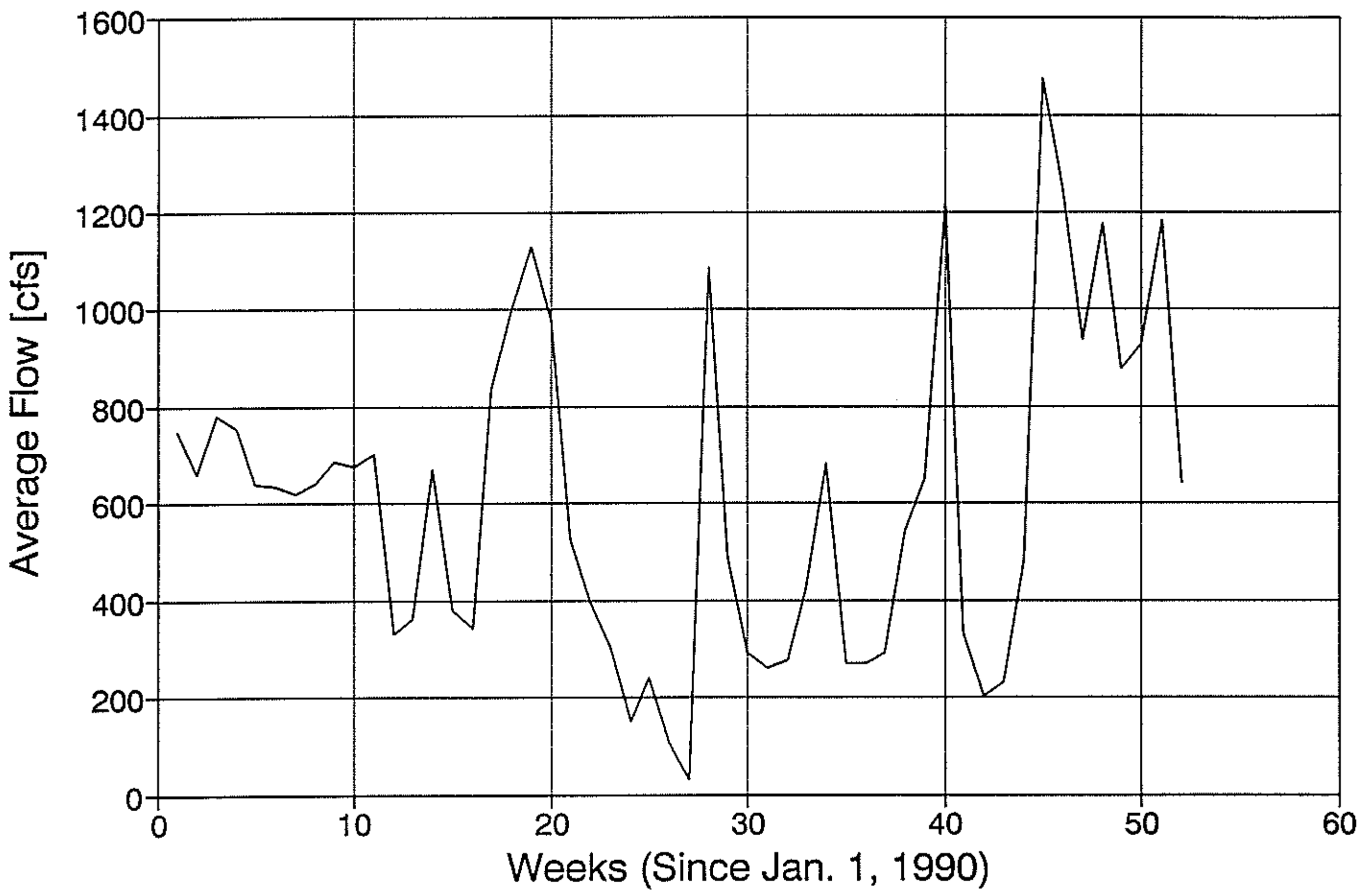

Fig. 6 Weekly Inflow to the RGP System at San Marcial, NM

were determined to fit the equations to elevation versus volume data for the two reservoirs. Results are shown in Figures 7 and 8.

Surface area was estimated from the elevation of each reservoir with equations of the form:

$$Area = D + E*Depth + F*Depth^2$$

where *Area* is the surface area in acres, *D*, *E*, and *F* are coefficients, and *Depth* is the depth of water in the reservoir in feet. The depth of water in each reservoir can be calculated by subtracting the bottom elevation of the reservoir from the elevation of the water surface. The coefficients were adjusted to make the equations fit surface area versus depth data for each of the reservoirs. Results are shown in Figures 9 and 10.

Weekly evaporation losses for each reservoir were calculated as follows.

$$Evap = EvapDepth_i * Area$$

where *Evap* is the evaporation loss in acre-feet, $EvapDepth_i$ is lake evaporation for week i in feet, and *Area* is the surface area of the reservoir in acre-feet. Monthly pan evaporation data were available for both Elephant Butte and Caballo reservoirs. Data were adjusted to provide estimates of weekly lake evaporation rates. Results are shown in Figure 11. Total lake evaporation for the year at Elephant Butte and Caballo reservoirs was estimated to be approximately 80 and 72 inches, respectively. Parameters used to describe the reservoirs in our model of the RGP are included in Table 2.

Our model of the RGP system includes four nodes located at Percha, Leasburg, Mesilla, and American Diversion dams. Flow in the river below each of these locations is estimated by our model. Because of the short connecting reach length, only two miles, the flow at

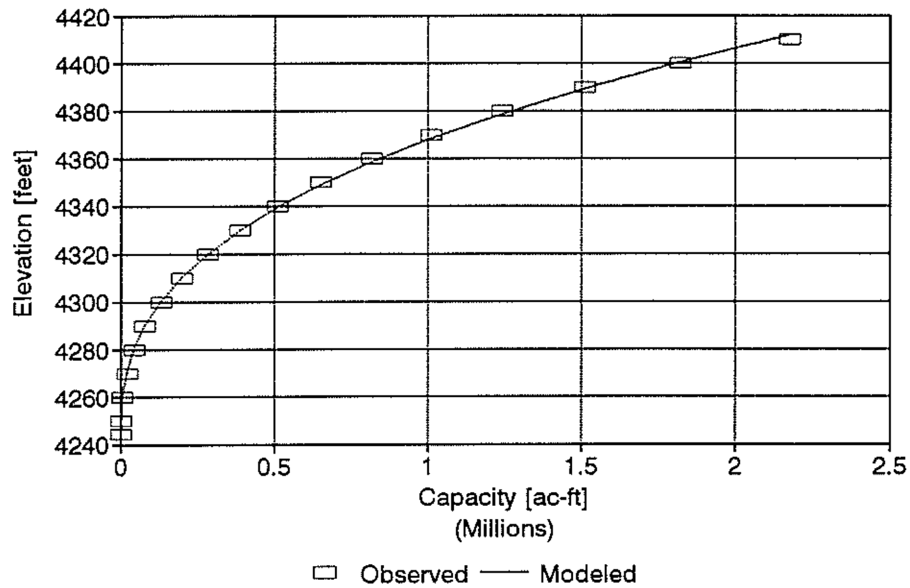

Fig. 7 Elevation versus Storage Volume for Elephant Butte Reservoir

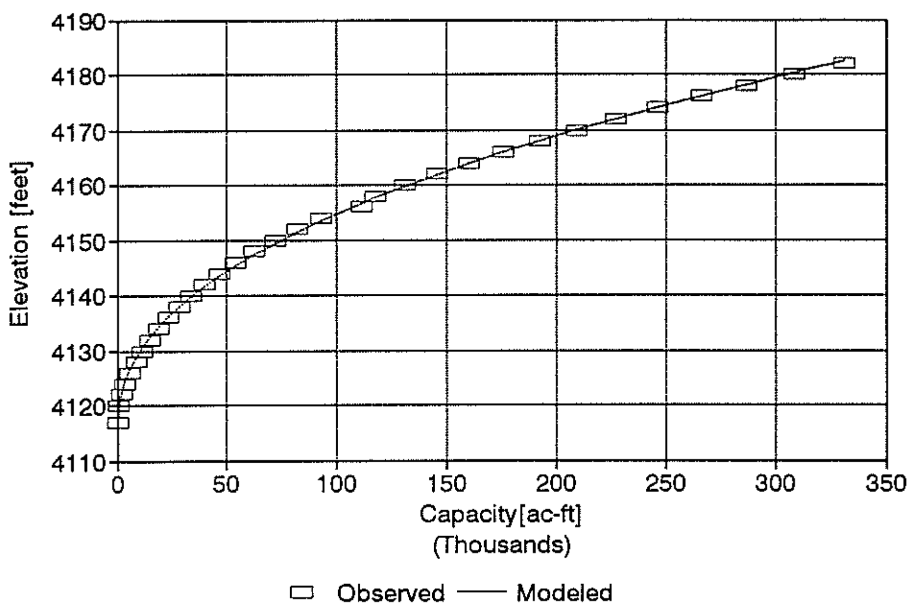

Fig. 8 Elevation versus Storage Volume for Caballo Reservoir

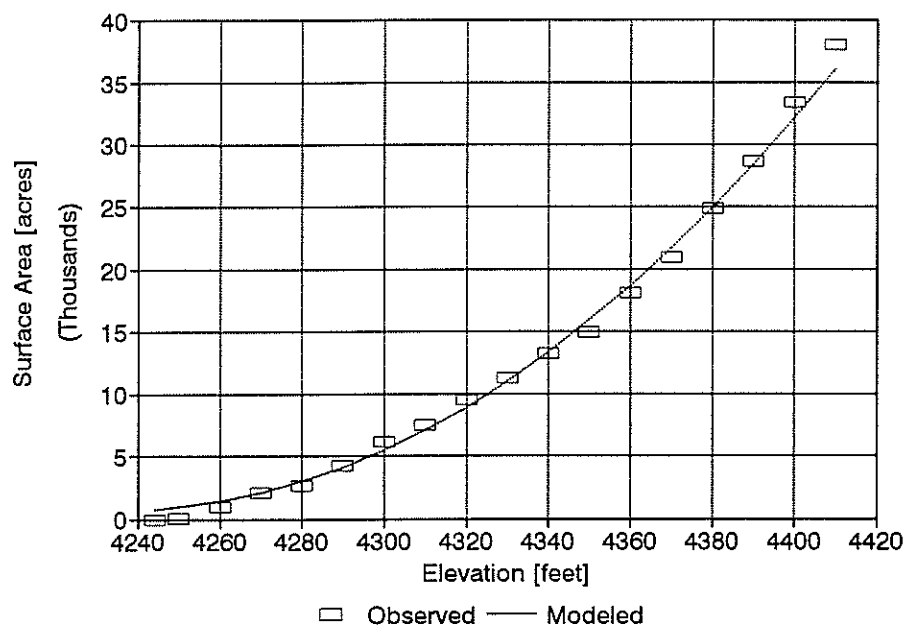

Fig. 9 Surface Area versus Elevation for Elephant Butte Reservoir

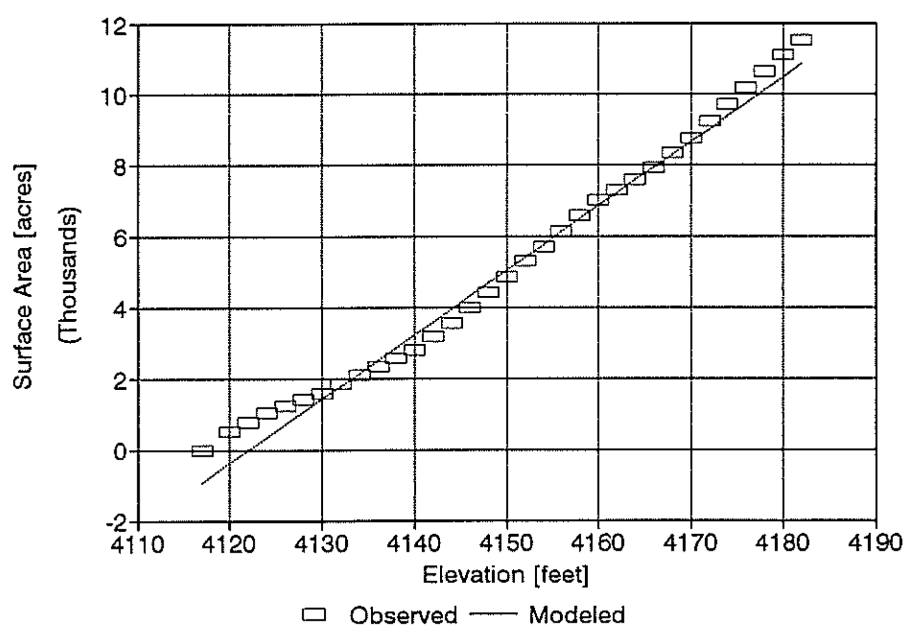

Fig. 10 Surface Area versus Elevation for Caballo Reservoir

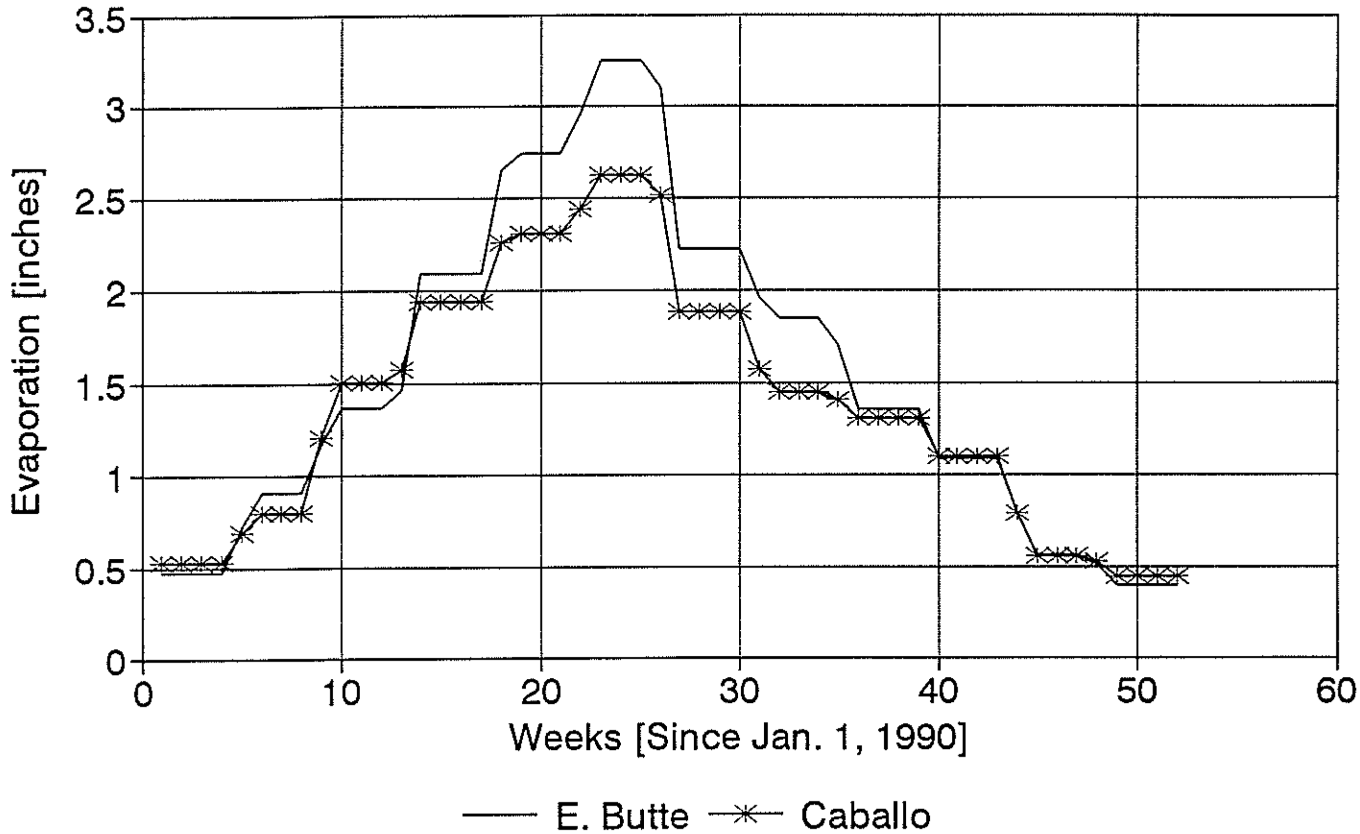

Fig. 11 Weekly Lake Evaporation Depth for RGP Reservoirs

Table 2 RGP Model Input Parameters

Historical Allotment	3	[acre-ft per acre]
Initial EB Volume	1676900	[acre-ft]
Initial Caballo Volume	70100	[acre-ft]

	Max.	Min.	
EB Volume	2065000	50000	[acre-ft]
Caballo Volume	245900	0	[acre-ft]

	Percha	Leasburg	Mesilla	American	
Initial Reach Inflow	2	46	46	60	[cfs]

Infeasibility Multiplier	1000	
Demand Penalty Multiplier	10	
Irrigation Efficiency	0.5	[-]

	Hist	Yield Funct Coef		Acerage	Ag Prices
Crop	Benefits	A	B	[acres]	[$/ton]
Vegetables	42796128	0	0	0	0
Pecans	42578570	0	0	0	0
Filed Crops	0	0.059	0.1943	24458	2352
Forage	0	-0.83	5.9207	19715	80.8
Cereals	0	-0.183	1.4665	2869	155.9

EOY EB Volume	1000000	[acre-ft]
EOY Penalty	1000	
EOY Multiplier	100	
Demand Penalty	100	

Hydro Power Variables			
Outlet Elevation	4207	[feet]	
Hydraulic Efficiency	1	[-]	
Turbine Efficiency Coef.	0.0232	0.00083	-2E-07
Min Generating Release	450	[cfs]	
Electric Rate	0.019	[$/KW-hr]	

Reservoir Variables	Coef_A	Coef_B	Coef_C	Coef_D	Coef_E	Coef_F	Base Elevation
Elephant Butte	0.566881	0.389978	4244.142	829.3456	9.277354	0.390115	4244.2
Caballo	0.232857	0.44507	4115.656	-926.83	90.55358	0	4117

Rec Benefits Variables	A	B	C
Elephant Butte 1	0	5.52	2.25E-06
Elephant Butte 2	-5.2E 07	65.06276	-1.4E-05
Caballo	0.001337	40.55002	-8.3E-05

Routing Parameters	Loss A	Loss B	Loss C
Mesilla	-12.1588	3.535302	-0.0678

	Musk C0	Musk C1	Musk C2	Musk Loss	Flow Min
Percha	1	0	0	0	0
Leasburg	0.499783	0.499783	0.000433	180.4703	46
Mesilla	0	0	0	-11.7861	46
American	0.4224	0.4224	0.155201	-115.591	0

Table 2 RGP Model Input Parameters (Cont.)

Inflow [cfs]	Percha Demand [cfs]	Leasburg Demand [cfs]	Mesilla Demand [cfs]	American Demand [cfs]	EB Lake Evap. [ft]	Caballo Lake Evap. [ft]
746.429	0	0	0	161.764	0.03967	0.04433
749.286	0	0	0	177.868	0.03967	0.04433
737.286	0	0	0	180.368	0.03967	0.04433
710.143	0	0	0	189.693	0.03967	0.04433
683.857	0.11429	0	0	220.265	0.06029	0.05714
652.286	0.2	0	0	252.785	0.07575	0.06675
651.286	0.2	0	0	284.256	0.07575	0.06675
660.143	65.6286	0	0	333.753	0.07575	0.06675
664.714	186.789	0	0.81714	561.743	0.09738	0.10047
689.571	221.516	82.5714	179.287	633.358	0.1136	0.12577
710	230.23	276.143	514.573	789.171	0.1136	0.12577
731.571	222.23	446	850.287	888.173	0.1136	0.12577
768	223.634	386	798.321	958.405	0.12229	0.13092
781.857	237.346	240.143	441.67	886.526	0.17443	0.16185
778.857	221.631	212.286	405.241	807.442	0.17443	0.16185
777.571	269.774	236.571	562.813	751.096	0.17443	0.16185
777.571	253.631	282.143	431.527	670.13	0.17443	0.16185
790.571	197.194	267.714	428.579	697.549	0.2208	0.18805
799	282.05	267.857	518.301	719.078	0.22853	0.19242
783.857	336.193	330.429	530.587	718.888	0.22853	0.19242
765.714	307.193	292.714	622.73	791.493	0.22853	0.19242
753.143	300.014	281.429	583.446	920.156	0.24679	0.20364
737	263.586	346	661.829	1098.05	0.27115	0.21859
713	269.586	381.286	792.114	1191.69	0.27115	0.21859
692.714	301.3	437.286	858.686	1220.58	0.27115	0.21859
677.143	317.211	444.857	862.724	1273.98	0.25891	0.20976
665.857	165.251	361.714	727.813	1326.06	0.18548	0.15674
654.857	95.2514	346.286	660.384	1260.87	0.18548	0.15674
638.143	121.109	344	647.241	1204.04	0.18548	0.15674
627.857	111.966	288.714	668.67	1184.57	0.18548	0.15674
623.714	182.644	285.429	562.206	1055.45	0.16298	0.13127
633	162.516	246.857	476.334	888.658	0.15397	0.12109
642.286	67.8014	234.714	442.049	702.505	0.15397	0.12109
638.143	89.23	241.429	431.334	724.606	0.15397	0.12109
633.571	202.23	288.857	553.503	855.489	0.1423	0.11764
634.286	145.873	327.857	688.781	789.698	0.11313	0.10901
632.429	198.73	283.286	565.924	647.624	0.11313	0.10901
627.143	170.301	258.429	507.781	499.577	0.11313	0.10901
605.143	95.1586	196.714	422.496	390.809	0.11313	0.10901
593.143	0	46	106.143	336.558	0.09115	0.0918
597.857	0	0	0	392.353	0.09115	0.0918
606.286	0	0	0	380.182	0.09115	0.0918
618	0	0	0	356.112	0.09115	0.0918
626.429	0	0	0	328.845	0.0658	0.06587
640.429	0	0	0	299.732	0.0468	0.04643
653.857	0	0	0	268.982	0.0468	0.04643
653	0	0	0	236.628	0.0468	0.04643
648	0	0	0	202.675	0.04287	0.04389
640.143	0	0	0	184.218	0.03307	0.03754
639.143	0	0	0	181.353	0.03307	0.03754
639.571	0	0	0	180.908	0.03307	0.03754
637	0	0	0	180.839	0.03307	0.03754

Percha was estimated as equivalent to the release from Caballo Reservoir. Flow below the other nodes was determined by routing flow from the upstream node and subtracting withdrawals. Two different procedures were used to rout flows. The first is based on the Muskingum routing procedure but adds an additional term to account for unmeasured channel losses (or gains) for each reach. Such losses or gains could be due to flow from unmonitored drains and arroyos to the river and water movement between the groundwater table and river. The modified Muskingum routing method we used was of the following form:

$$Q_{i+1} = C_0 * I_{i+1} + C_1 * I_i + C_2 * Q_i - Loss$$

where Q_{i+1} is the outflow from the reach for week $i+1$ in cfs, I_{i+1} is the inflow to the reach for week $i+1$ in cfs, I_i is the inflow in cfs for the previous week, Q_i is the outflow from the reach for week i, *Loss* is the channel loss in cfs, and C_0, C_1, and C_2 are Muskingum routing parameters. The channel loss represents unaccounted water loss or gain in the reach. Values for C_0, C_1, C_2, and *Loss* were varied in order to find a set of parameters that approximated 1990 flow data. Results are shown in Figures 12 and 13. These figures were generated with historical inflows to each reach.

For the reach from Leasburg to Mesilla Dam, a different method was used to calculate the outflow of the reach. The Muskingum routing procedure was unable to provide good flow estimates for this reach. This may have been due to a large amount of unmeasured return flow to the channel in this reach. Such return flow could be due to irrigation drains and seepage from the groundwater table. Both these sources are seasonal, making it very difficult to represent flow in the reach with a constant loss parameter as described in the previous method. For this reach, a mass balance approach was applied. Outflow from the

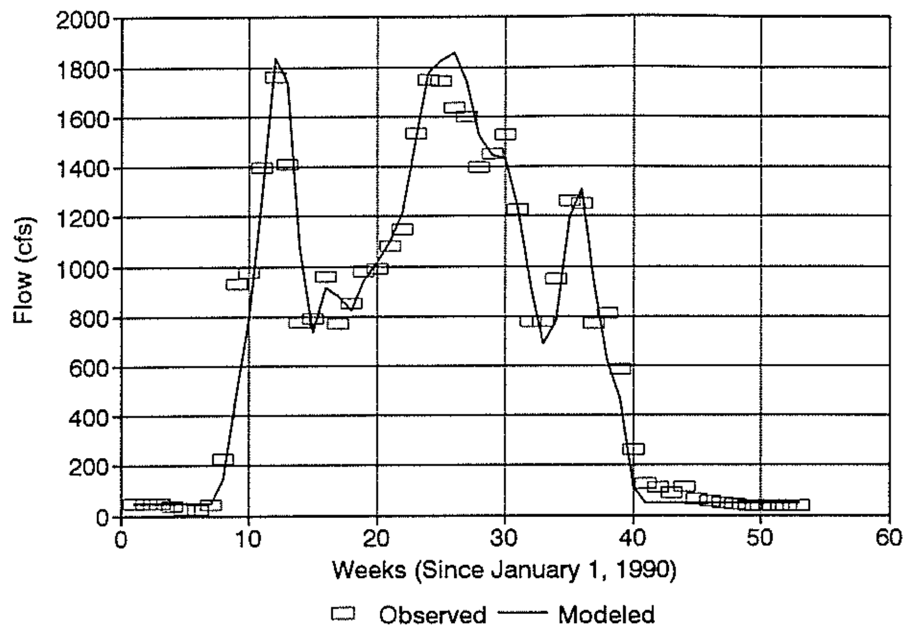

Fig. 12 Observed and Modeled Flows at Leasburg Dam

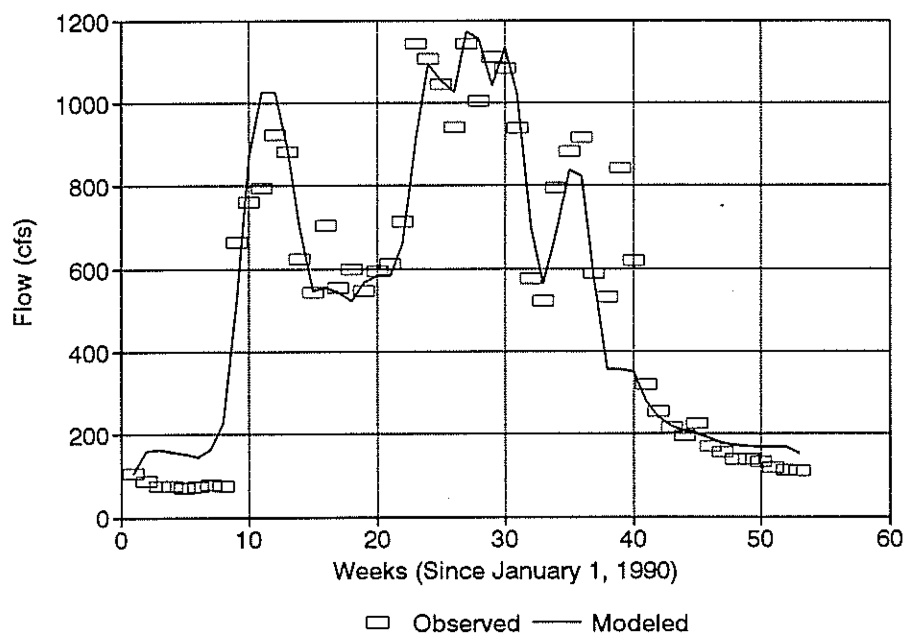

Fig. 13 Observed and Modeled Flows at American Dam

reach was estimated by the following equation:

$$Q_i = I_i - Loss_i$$

where Q_i is the outflow from the reach for week i in cfs, I_i is the inflow for the week in cfs, and $Loss_i$ is the channel loss for the week in cfs. Weekly channel losses were assumed to be of the form:

$$Loss_i = A + B*Week_i + C*Week_i^2$$

where $Week_i$ is the week of the year and A, B, and C are fitting parameters. The fitting parameters were adjusted to fit the historical flow data for the reach from Leasburg to Mesilla Dam. The results are shown in Figures 14 and 15.

The behavior of our computer model was similar to that of the actual RGP system. When the model is provided with the historical operating policy used for 1990, the flow at American Dam was estimated as shown in Figure 16. This figure also shows the actual flows at American Dam for 1990. Comparison of the two flow series demonstrates how closely our model reflects the RGP system. As can be seen from the figure, the model appears to have done a reasonable job of representing the RGP system. Any differences in the two flow series were due to inaccuracies in the model. Since American Dam represents the last node in the model, errors from all upstream portions of the model are reflected in the estimate of flow at this point.

Although our model did not provide a completely accurate picture of RGP operation, it retained much of the complexity of system operation. To make the model truly representative of the RGP system would require much additional research beyond the scope of this effort. Our model based on the RGP system, however, was adequate for our

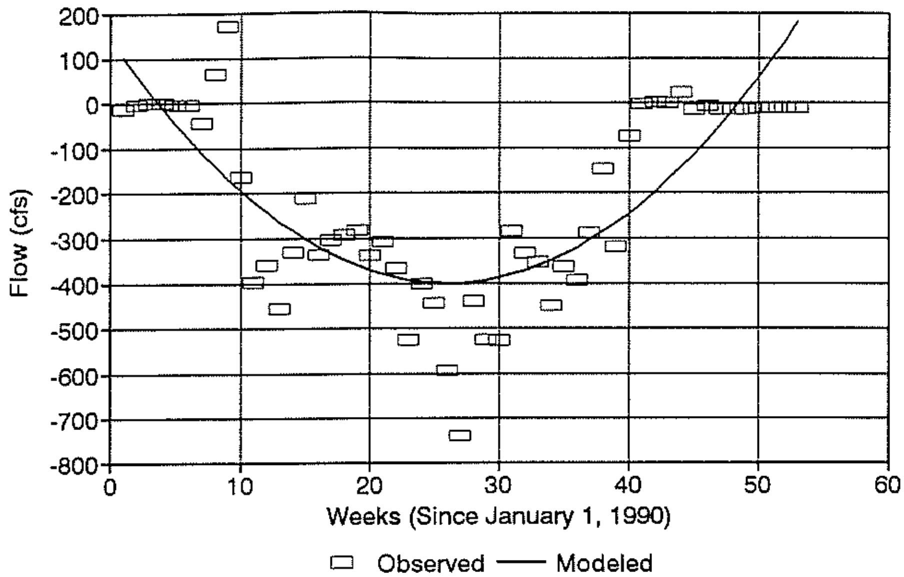

Fig. 14 Weekly Losses in the Reach from Leasburg to Mesilla Dam

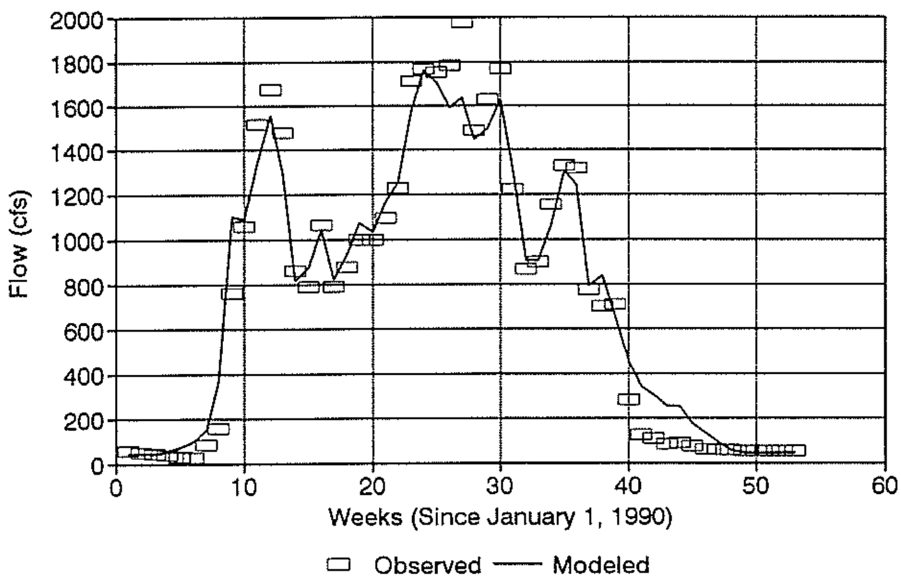

Fig. 15 Observed and Modeled Flows at Mesilla Dam

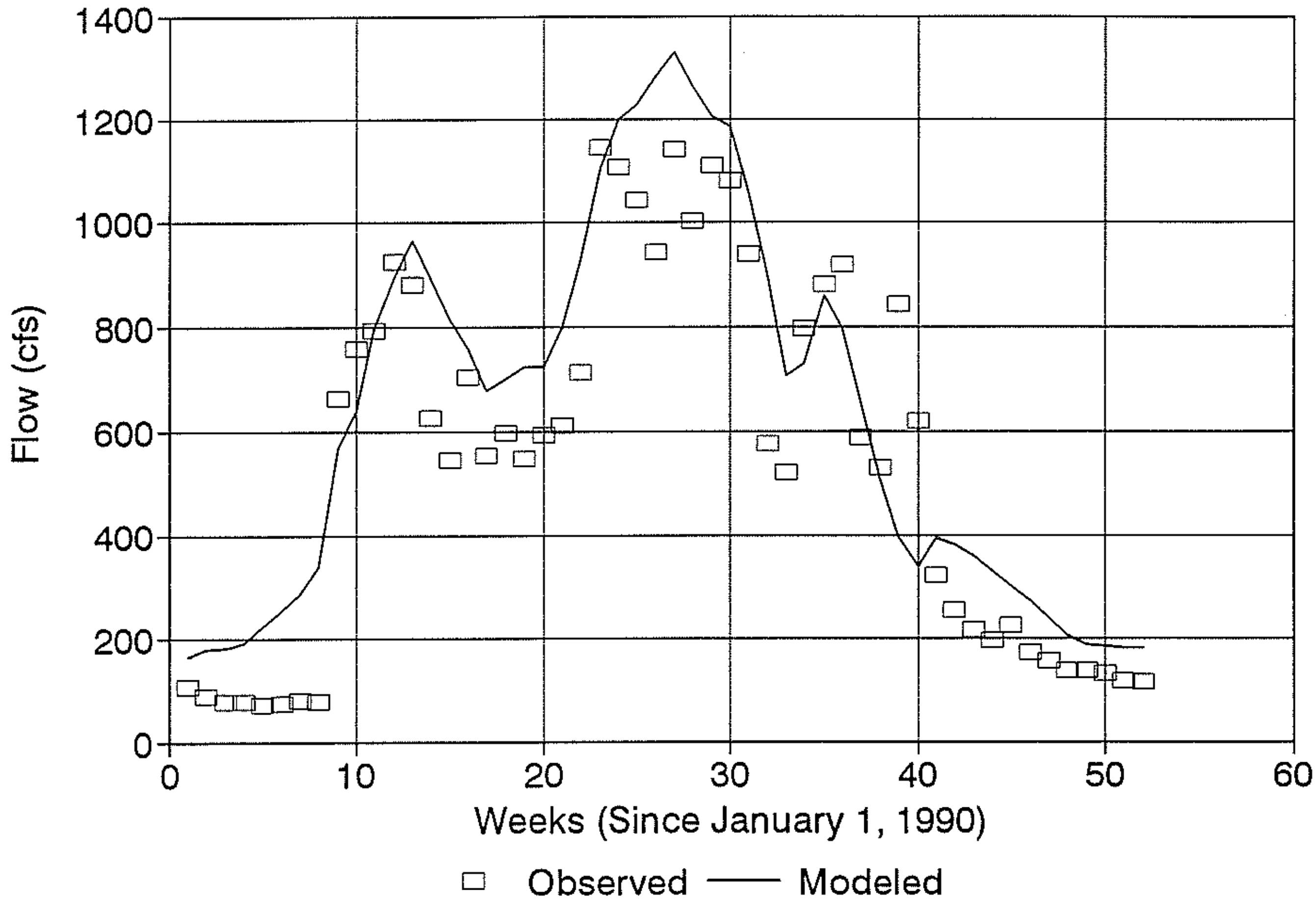

Fig. 16 Observed and Modeled Flows at American Diversion Dam

purposes. We wanted to investigate the potential of a genetic algorithm to guide the search for optimal operating strategies for a relatively complex water resources system. Because our model was limited in its ability to simulate accurately the RGP system, the results of optimization should not be taken as best for the actual RGP system. This limits the contribution of this effort to general insights regarding actual system operation. Our results are most useful for examining the ability of a genetic algorithm to guide the search for optimal operating policies if a truly representative model could be developed. This is the context in which our results should be evaluated.

Economic Modeling of the RGP System

The total economic benefit of an operating strategy was determined by the following equation:

$$B_{Total} = B_{Ag} + B_{Rec} + B_{Hydro} - P_{Demand} - P_{Infeas} - P_{EOY}$$

where B_{Total} is the total economic benefits associated with an operating strategy, B_{Ag}, B_{Rec}, and B_{Hydro} are the agricultural, recreational, and hydroelectric benefits respectively, and P_{Demand}, P_{Infeas}, and P_{EOY} are the penalties for violating demand, infeasability, and end of year operating constraints. All variables have units of dollars.

Agricultural benefits for the model were based on benefits generated by five categories of crops: vegetables, pecans, field crops, forage, and cereals. EBID reports crop area and value for these five categories in their annual operating plans. Vegetables included such crops as peppers, onions, lettuce and cabbage. Field crops were primarily upland and pima cotton. Forage represented alfalfa and silage crops. Cereals included wheat, barley, and sorghums.

Two different methods were used to estimate agricultural benefits for these categories. Both methods used the yearly water allocation as part of the estimate. When available, crop water production functions were used. Sammis et al, (1979) provides such functions for conditions in New Mexico for alfalfa, cotton, and grain sorghum. These functions were used to estimate yields for the forage, field crops, and cereals categories. Yield functions were of the form:

$$Yield = A + B * ET$$

where *Yield* is in units of tons per acre, *A* and *B* are coefficients, and *ET* is the crop consumptive use (or evapotranspiration) in feet of water. Assuming an irrigation efficiency of 50%, crop consumptive use was estimated to be half the yearly allotment of water. After determining the yield for each category, benefits were calculated with the following formula:

$$Benefits = Yield * Area * Value$$

where *Benefits* are in dollars, *Yield* is in tons/acre, *Area* is in acres, and *Value* is in dollars per ton. Average values for the various categories of crops were determined by dividing the historical benefits by the historical yields and areas.

Yield functions were not available for the vegetable and pecan categories. For these crop categories, agricultural benefits were assumed to be linearly related to the allotment. The following equation was used to estimate agricultural benefits:

$$Benefits = \frac{Allotment}{Historical \quad Allotment} * Historical \quad Benfits$$

where *Benefits* are in dollars, *Allotment* and *Historical Allotment* are in feet of water per acre of water-righted land, and *Historical Benefits* are in dollars.

The data used for calculating agricultural benefits are included in Table 2. Using this method, the estimated total agricultural benefits for 1990 amounted to $118,640,016. This compares quite well with the reported agricultural benefits for 1990, which were $119,293,879. Figure 17 shows the relationship between water allotment and agricultural benefits as generated by our model of RGP agricultural benefits.

Recreational benefits for the model were determined with the help of the RIOFISH (Cole et al, 1990) software. This package operates on a monthly time step and estimates the recreational value of sportfishing. The package can be used to evaluate the operation of the three major river systems in New Mexico in their entirety or only a portion of a river system. In this case, operation of only Elephant Butte and Caballo reservoirs were considered.

Annual benefits for various volumes of Elephant Butte Reservoir were determined by maintaining a constant reservoir level for the entire year of the RIOFISH model run.

Table 3. Annual Angler Benefits for Various Volumes of Elephant Butte Reservoir

Elephant Butte Volume [acre-feet]	Caballo Volume [acre-feet]	RIOFISH Angler Benefits [$]	Normalized Angler Benefits [$]
0	50,000	-12,814,000	0
50,000	50,000	-11,785,000	1,029,000
500,000	50,000	-9,140,000	3,674,000
1,000,000	50,000	-5,046,000	7,768,000
1,250,000	50,000	-3,071,000	9,743,000
1,500,000	50,000	524,000	13,338,000
1,750,000	50,000	5,188,000	18,002,000
2,000,000	50,000	7,886,000	20,700,000
2,100,000	50,000	8,719,000	21,533,000

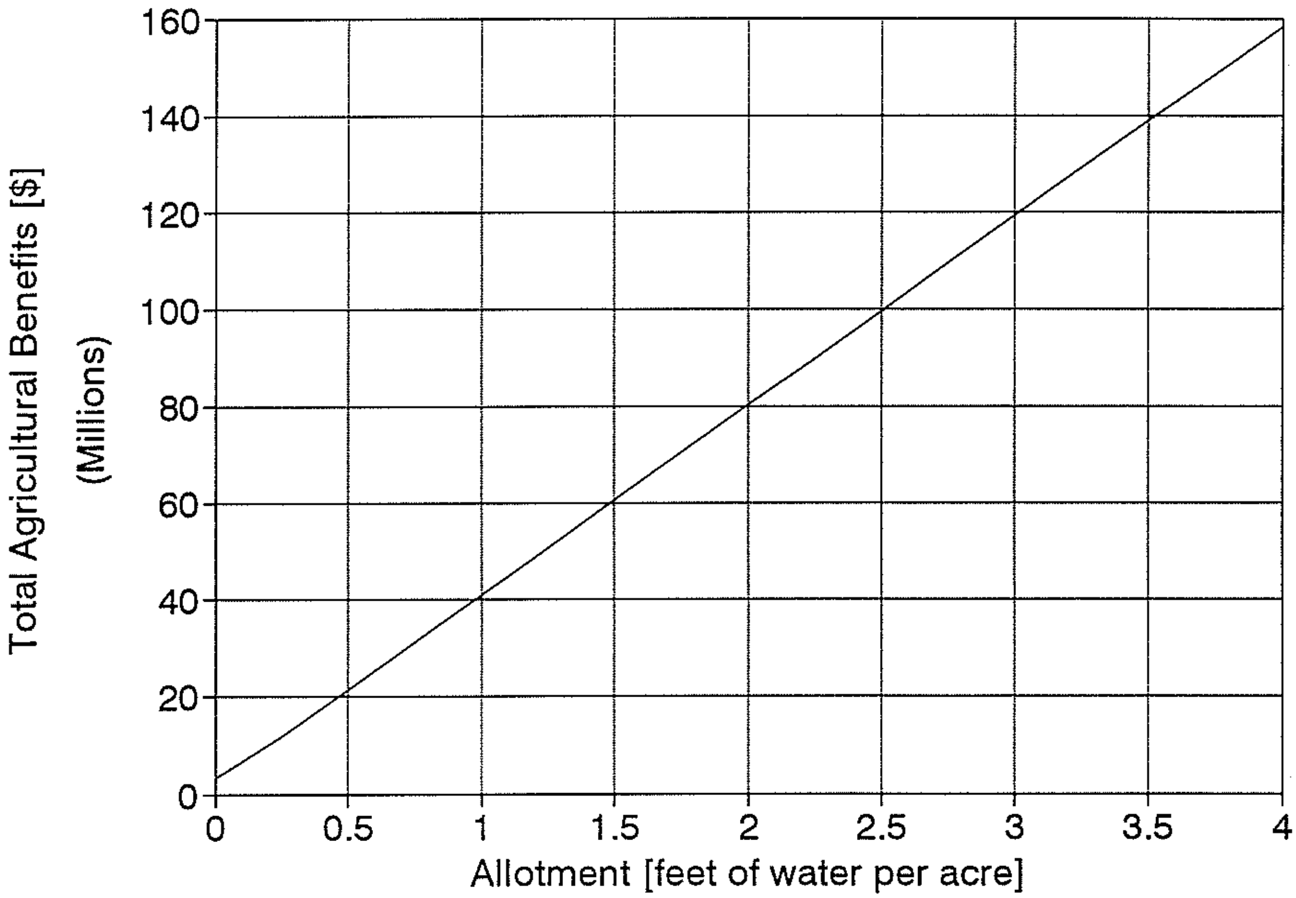

Fig. 17 Agricultural Benefits for Model as a Function of Total Water Allotment

Historical settings for 1990 were used for all other program parameters. The storage volume of Caballo Reservoir was held at a constant value of 50,000 acre-feet for all runs. Table 3 (shown previously) displays the results of the runs. Results were normalized by adding a constant value of $12,814,000 to the value of all runs. This resulted in a value of $0 dollars if the reservoir was empty and roughly 21.5 million dollars if held at its maximum volume of 2.1 million acre-feet for the year.

Figure 18 shows the normalized values of annual angler benefits as a function of storage volume in Elephant Butte Reservoir. Two formulas were used to model this relationship. For storage volumes less than 1.5 million acre-feet, angler benefits were estimated by the following equation:

$$Angler\ Benefits = 5.52 * Volume + 2.25x10^{-6} * Volume^{2}$$

For storage volumes greater than 1.5 million acre-feet, the equation below was used:

$$Angler\ Benefits = -5.2x10^{7} + 65.06 * Volume - 1.4x10^{-5} * Volume^{2}$$

In both of the previous equations, *Angler Benefits* is yearly angler benefits in dollars and *Volume* is the storage volume of Elephant Butte Reservoir in acre-feet. These equations were used to estimate the angler benefits for a specific volume of Elephant Butte during each time step of the model run. Since these equations give annual benefits, the value obtained was divided by 52 in order to get an estimate of the weekly benefits.

A similar methodology was used to determine the angler benefits for Caballo Reservoir. The RIOFISH program was run for 1990 for various volumes of Caballo Reservoir with the volume of Elephant Butte Reservoir held at a constant 1.75 million acre feet. Table 4 shows the results of these runs.

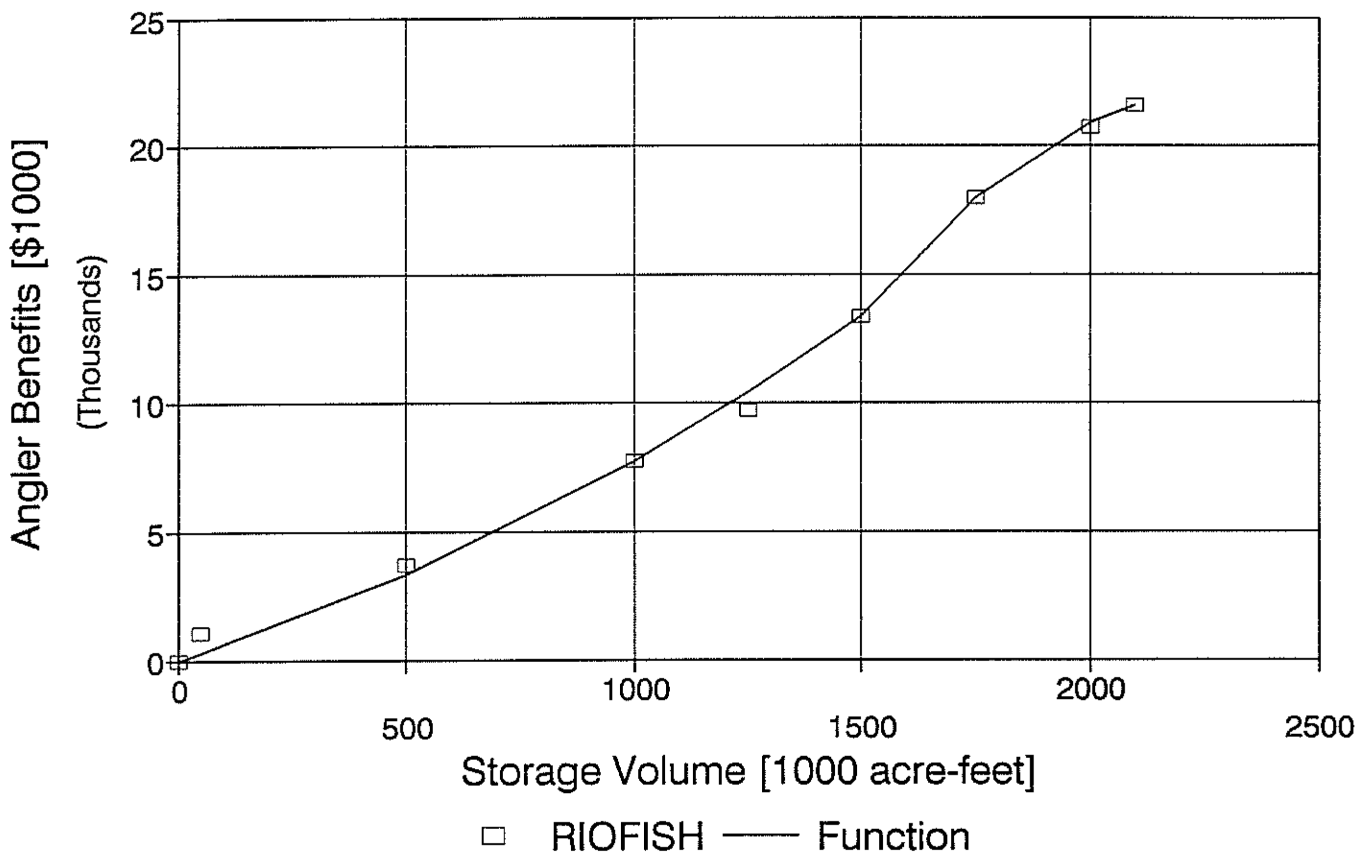

Fig. 18 Elephant Butte Angler Benefits from RIOFISH and Function

Angler benefits for Caballo Reservoir were estimated by the following equation:

$$Angler\ \ Benefits = 1.34x10^{-3} + 40.55 * Volume - 8.3x10^{-5} * Volume^{2}$$

In this equation, *Angler Benefits* are again in dollars and *Volume* is the storage volume of Caballo Reservoir in acre-feet. Figure 19 shows the data for angler benefits from the RIOFISH runs and the equation developed to fit this data.

Because recreational benefits estimated by RIOFISH are for angler benefits only, total recreational benefits would be more. The RIOFISH model estimated angler days for the two reservoirs to be approximately 500,000. According to EBID's annual report for 1990, visitor days to the state parks in the RGP amounted to 2.1 million visitor days. Therefore, total recreational benefits were estimated to be four times angler benefits.

Table 4. Annual Angler Benefits for Various Volumes of Caballo Reservoir

Caballo Volume [acre-feet]	Elephant Butte Volume [acre-feet]	RIOFISH Angler Benefits [$]	Normalized Angler Benefits [$]
0	1,750,000	3,668,000	0
10,000	1,750,000	4,078,000	410,000
25,000	1,750,000	4,650,000	982,000
50,000	1,750,000	5,312,000	1,644,000
75,000	1,750,000	6,371,000	2,703,000
100,000	1,750,000	6,985,000	3,317,000
125,000	1,750,000	7,527,000	3,859,000
150,000	1,750,000	7,823,000	4,155,000
175,000	1,750,000	8,074,000	4,406,000
200,000	1,750,000	8,364,000	4,696,000
230,000	1,750,000	8,706,000	5,038,000

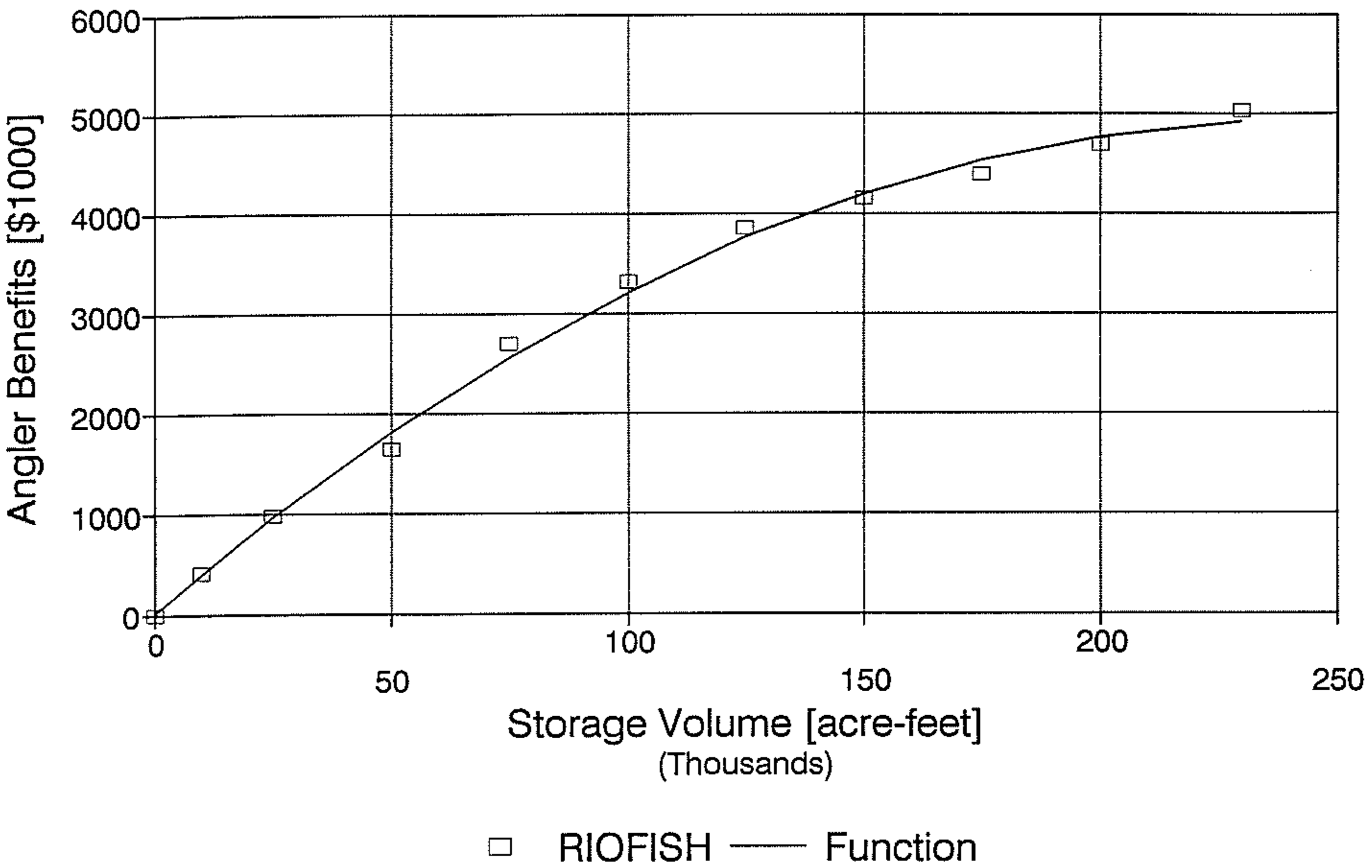

Fig. 19 Caballo Angler Benefits from RIOFISH and Function

We also investigated using a multiplier of ten in order to estimate total recreation benefits from angler benefits. A factor of this size makes recreational benefits of approximate equal value to agricultural benefits. This was desirable to test the genetic algorithms ability to optimize the operation of a water resources system with truly competing water demands. The current system appears to have a heavy emphasis on agricultural benefits that tends to dominate the other uses of water. We are not suggesting that recreation should be valued in this way for the RGP. This weighting was used simply to make recreational and agricultural benefits of approximately equal value, insuring a system with truly competing demands.

Hydroelectric power generation from Elephant Butte Reservoir was calculated with the following formula:

$$Power = 0.7457 * \frac{\gamma * Q * H * e}{550.0}$$

where *Power* is in kilowatts, *0.7457* is a conversion factor from horsepower to kilowatts, γ is the weight of water in pounds per cubic foot, Q is the flow in cfs, H is the net operating head in feet, e is the efficiency of the turbines, and *550.0* is a factor to convert from units of foot-pounds per second to horsepower.

Net operating head was defined by the following formula:

$$H = \frac{Elev_{Res} - Elev_{Out}}{h}$$

where H is the net operating head, $Elev_{Res}$ is the water surface elevation in Elephant Butte Reservoir in feet, $Elev_{Out}$ is the elevation of the power plant outlet in feet, and h is the hydraulic efficiency. After conversing and corresponding with Bill Neiley of the US Dept.

of Interior, Bureau of Reclamation, we determined values for the outlet elevation of 4210.26 feet and a hydraulic efficiency of one.

Turbine efficiency was also estimated with the help of Mr. Neiley. The following formula was used to estimate turbine efficiency as a function of the release flow:

$$e = 0.0232 + 0.00083 * Q - 2x10^{-7} * Q^2$$

where e is the turbine efficiency and Q is the flow through the turbines. Figure 20 shows the relationship of turbine efficiency as a function of flow through the turbines. A minimum flow of roughly 450 cfs is required to operate the turbines.

Total hydroelectric benefits for a week of operation were estimated by the following formula:

$$Benefits = 168 * Power * Rate$$

where *Benefits* is the hydroelectric benefit for a week of operation in dollars, *168* is the number of hours in a week, *Power* is the hydroelectric generation rate in kilowatts, and *Rate* is the value of electricity in dollars per kilowatt-hour. We assumed an average value of $0.019 per kilowatt-hour for the electric rate.

This model predicted a value of $1,918,847 for the total hydroelectric benefits of the historical operating policy for 1990 with a total generation of roughly 101 million kilowatt hours. This compares reasonably well with the actual reported hydroelectric generation for 1990 of 70 million kilowatt hours.

Penalties were imposed on any operating strategies that failed to meet system operating constraints. These constraints included demand constraints for agricultural delivery, demand constraints for interstate and international treaty compliance, minimum and maximum

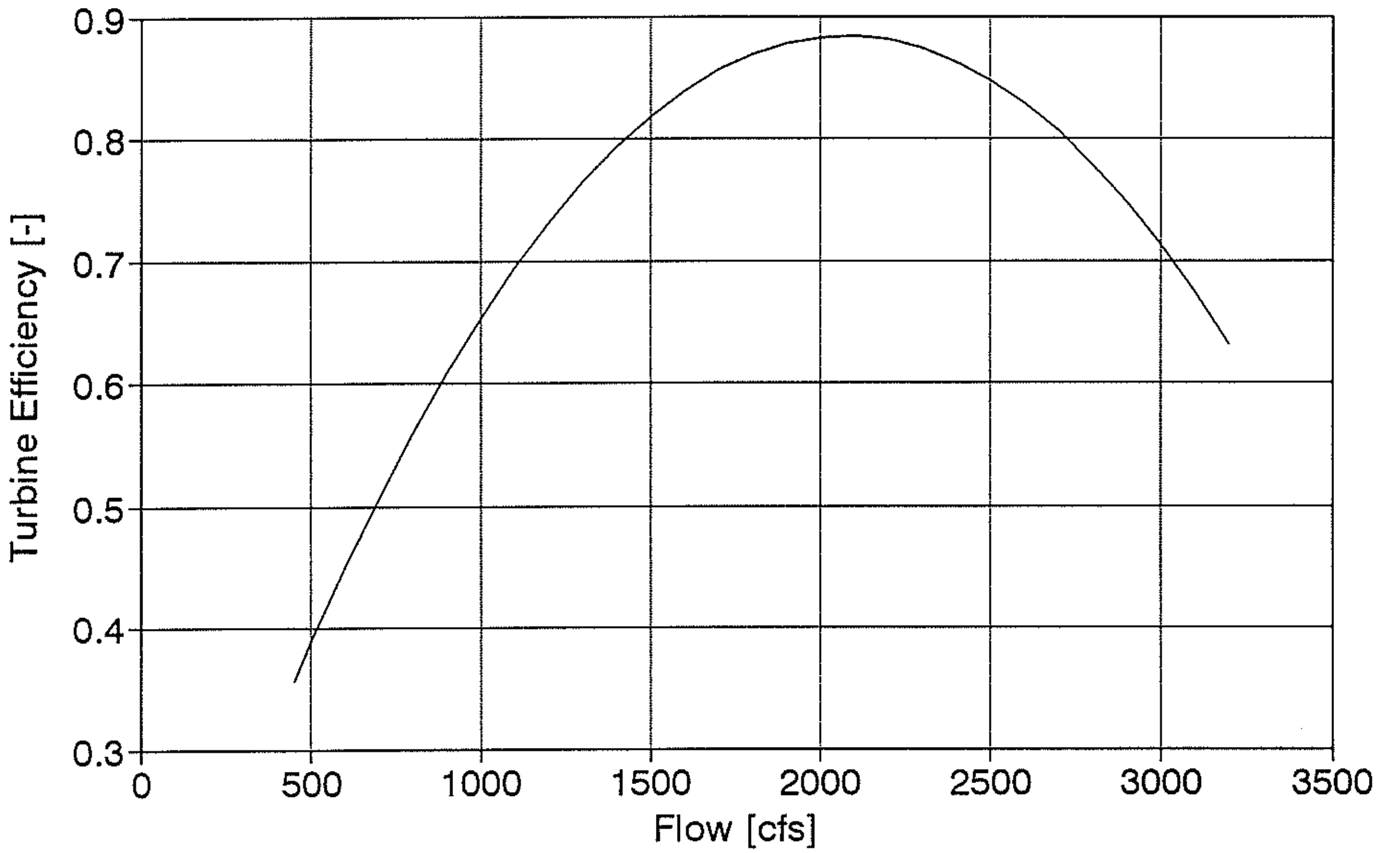

Fig. 20 Turbine Efficiency as a Function of Flow

volumes in the two storage reservoirs, and minimum end of year storage volumes in the reservoirs. These penalties, essentially negative benefits, acted to decrease the value of operating policies that violated operating constraints. No attempt was made to insure that these penalties represented the true economic cost of constraint violation. Instead, these penalties were merely adjusted until large enough to prevent the genetic algorithm from favoring operating strategies that violated constraints.

The model supplied water to four points representing Percha, Leasburg, Mesilla and American dams. Agricultural demands within the RGP in southern New Mexico were met by withdrawals from the river at the first three points mentioned above. Water deliveries for downstream irrigation districts and for treaty compliance with Mexico were at American Dam. Weekly demands for the three diversion points in New Mexico were calculated from historical withdrawal data obtained from Elephant Butte Irrigation District. Historical flow data at American Dam were available but were not used for the weekly demands at this point. Instead, demands were set equal to 2 cfs less than the model generated flows for the historical operating policy. This procedure insured the historical operating policy could meet the system demands. Due to model inaccuracies, the historical operating policy could not meet the historical operating demands at American Dam. The flow at American Dam was assumed to be adequate for meeting demands for treaty compliance with Mexico and downstream irrigation districts.

Weekly penalties imposed at each node for not meeting demands were of the following form:

$$P_{Demand}=D_{Mult}*(Flow_i-Demand_i)^2$$

where P_{Demand} is the penalty in dollars for failing to meet the demand, D_{Mult} is a demand penalty multiplier, $Flow_i$ is the flow in the river during week i at the diversion point in cfs, and $Demand_i$ is the required withdrawal in cfs at the point for week i. These penalties were imposed every week at each node where demand was not satisfied and accumulated throughout the model run. The shape of this penalty function was intended to greatly increase the penalty for strategies that violated demand constraints by larger amounts. The demand penalty multiplier was adjusted until its size discouraged the genetic algorithm from favoring strategies that failed to meet demands at the supply nodes.

Operating strategies that resulted in reservoir volumes above the maximum volume or below the minimum volume for each reservoir were assumed to be infeasible. The strategies were penalized in the following manner:

$$P_{Infeas} = I_{Mult} \left(1 - \frac{Week}{104} \right)$$

where P_{Infeas} is the penalty for an infeasible solution in dollars, I_{Mult} is an infeasability penalty multiplier, and $Week$ is the week of the model run during which the infeasibility was discovered. The shape of this penalty function was intended to increase the penalty associated with strategies that became infeasible earlier in the model run. Penalties for infeasibility in the last week of the year of operation were roughly half those for strategies proving infeasible in the first week of operation. The infeasibility multiplier was adjusted to eliminate infeasible solutions from the genetic algorithm search. The model run was terminated after an infeasibility was detected and penalized.

A final penalty was imposed if the operating strategy resulted in reservoir volumes below certain values at the end of each year. These penalties were of the form:

$$P_{EOY} = EOY_{Mult} * (Volume_{52} - Volume_{EOY})^2$$

where P_{EOY} is the penalty in dollars for not finishing the year at or above a specified minimum volume level, EOY_{Mult} is an end of year penalty multiplier, $Volume_{52}$ is the volume of the reservoir for week 52 in acre-feet, and $Volume_{EOY}$ is the specified minimum end-of-year reservoir volume in acre-feet. A minimum end-of-year storage volume of one million acre-feet was imposed at Elephant Butte Reservoir. No end-of-year minimum was imposed at Caballo Reservoir.

Genetic Algorithm

We made use of a commercially available genetic algorithm software package (GENEtic Search Implementation System or GENESIS, Version 5.0) to guide the search for optimal strategies. This software was developed by John J. Grefenstette to promote the study of genetic algorithms as function optimizers. GENESIS was written in the C programming language for use on DOS or UNIX based computers. This system handles the basic tasks of genetic algorithm search, including encoding problem variables as binary strings, creation of an initial population, implementation of genetic operators, and collection of search data. The user must specify the options and parameters for genetic search and provide an evaluation function that determines the fitness of strings. In this case, the simulation model of the RGP and estimation of economic benefits was used to determine the fitness.

Operating policies for the RGP were translated to bit strings by the GENESIS software. Policies specified the management decisions required for weekly operation of the RGP over a one-year period. These included the annual allocation to the irrigation districts (in acre-feet) and weekly releases from the two supply reservoirs (in cfs). This added up to a total of 105 decision variables for the model period. Yearly irrigation allocations from 0 to 4 feet per acre were considered in increments of 3/4 inches. Reservoir releases between 0 and 3200 cfs were optimized in increments of 12.5 cfs. This resolution of decision variables was sufficient to meet operating needs for the RGP. Yearly allocations were represented with a string segment of six bits (sixty-four possible states between 0 and 4 acre-feet). Weekly releases were represented with a string segment of eight bits (256 possible states between 0 and 3200 cfs). This resulted in binary strings with 838 bits to represent operating policies.

The genetic algorithm guided the search of possible operating policies using the net economic benefit as the fitness of each string. To determine economic benefit, each bit string was first translated into the operating policy that it represented. This policy was then supplied to the computer model of the RGP in order to predict the response of the system and the economic benefit of the policy. The total economic benefit was then returned to the genetic algorithm as the fitness of the string. Water uses could be prioritized by arbitrarily increasing (or decreasing) the economic benefit of individual water uses before returning the net economic benefit to the genetic algorithm.

During the preliminary optimization runs, we experimented with various values of genetic algorithm search parameters and penalty coefficients. In previous research efforts, we have made use of search parameters identified by Grefenstette (1986) as providing best performance for a variety of search problems. These parameters provided excellent performance for preliminary runs and were retained for the remainder of this effort. These parameters included a population size of 30, crossover and mutation rates of 0.95 and 0.01, respectively, generation gap and scaling window of one, and an elitist selection strategy. Penalty functions were adjusted during the preliminary runs until the search no longer favored strategies with undesirable performance.

Also during our preliminary runs, we determined that the genetic algorithm was not able to optimize efficiently the yearly irrigation allocation. Genetic algorithm runs would converge on operating strategies with small values for the allocation such as 2.5 feet. Further search did not result in improved economic performance. Operating strategies with larger allotments, such as the historical operating strategy, were known to exist. We suspected that the genetic algorithm search was not able to reach these higher benefit regions of the search space because allotments and releases are closely linked for a good operating strategy. An efficient genetic algorithm based search requires that small changes in the binary strings result in measurable improvement in string performance. This principle is violated in this arrangement. For our runs, smaller allocations can more easily avoid demand penalties. Once an operating policy that avoids these penalties is found, the genetic search does not readily progress to larger allotments. Movement to a larger allotment without a corresponding increase in every release variable would result in large demand penalties. Such sweeping changes in the binary strings are improbable, slowing down the progress of the search considerably. It was concluded that it is inefficient to allow the genetic algorithm to optimize the allotment. For the remainder of our runs, we specified the allotment and allowed the genetic algorithm to optimize the releases for this allotment.

RESULTS

The results of the application of genetic algorithm search to both the simple exercise we considered and the optimization of the complex model based on the RGP proved quite promising.

DYNAMIC PROGRAMMING VERSUS GENETIC ALGORITHM COMPARISON

Once the data were gathered from the application of both dynamic programming and genetic algorithm techniques to the simple exercise, they were evaluated in terms of computer run time and exercise complexity. Dynamic programming running time increased exponentionally as the complexity increased, while the genetic algorithm's running time increased linearly. Recall that the exercise complexity grew in terms of stages and states within stages. There was little difference between dynamic programming and genetic algorithms in the smaller capacity and states scenarios. Dynamic programming ran more effectively (shorter run time to reach optimal solutions) than genetic algorithms in the smaller capacity and states scenarios. However, as the capacity and states increased, dynamic programming running time increased dramatically, while genetic algorithms running time increased at a significantly slower rate.

As expected, dynamic programming found global optimum solutions for all scenarios. Genetic algorithms found global optimum solutions for smaller scenarios, but as the scenario size increased, genetic algorithms found only near optimum solutions (see Fig. 21). Although these results indicate that dynamic programming performed more consistently than genetic algorithms, it is important to consider the trade offs of time, accuracy, and flexibility of each technique. Genetic algorithms offered greater flexibility in less time, as they imposed no constraints on the way the system was simulated, nor was it significantly affected by the size of the problem. Further research is needed to determine when optimum solutions are required and when near optimum solutions will be sufficient.

To carry out this comparison we used a backward dynamic programming formulation. Another alternative would be a forward dynamic programming formulation which, some might argue, would have been more efficient. For our purposes, there is little difference in the forward and backward techniques because the overall outcome and inherent problems would be the same.

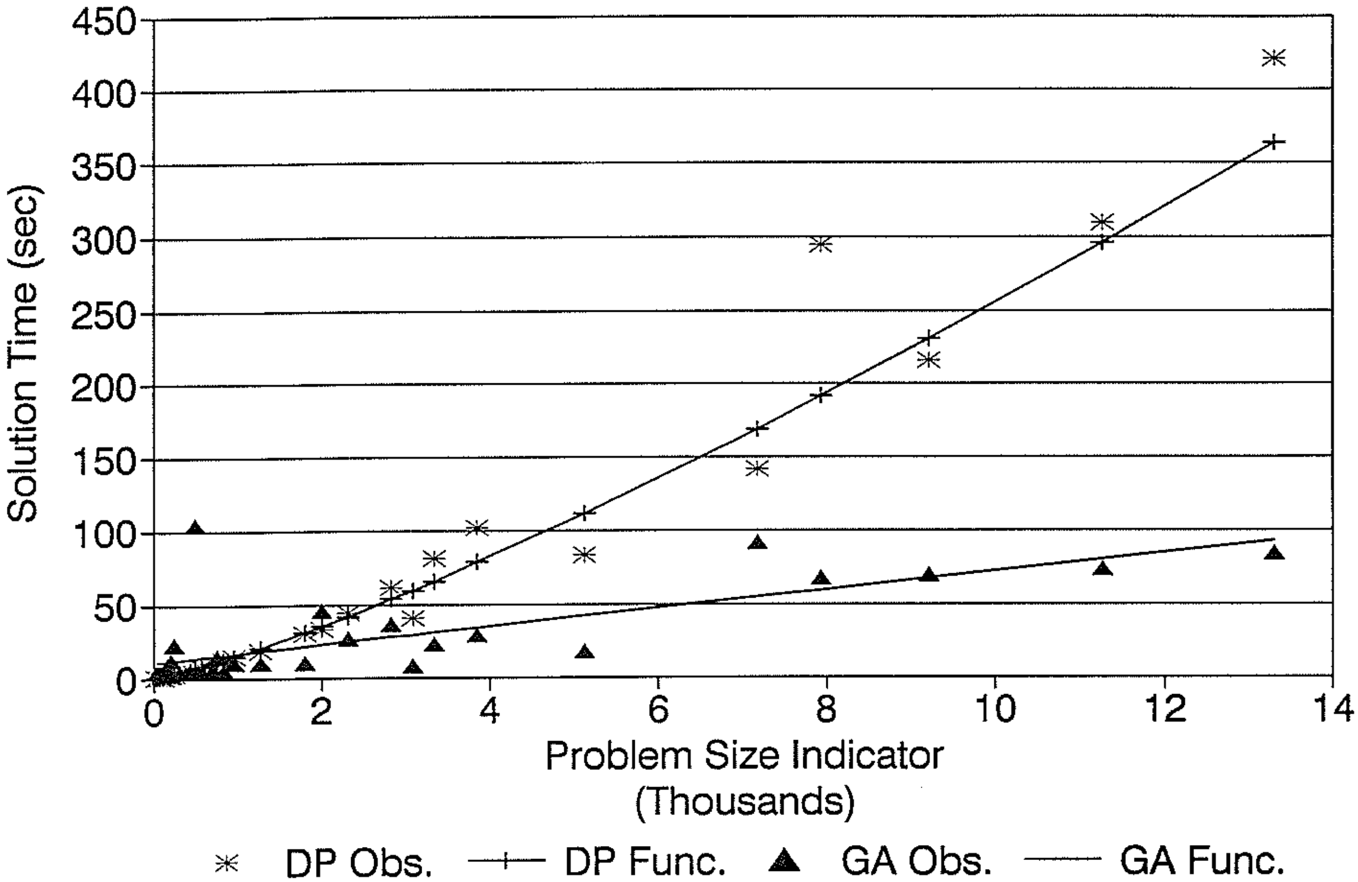

Fig. 21 Comparison of Dynamic Programming and Genetic Algorithms

Another way to increase the size of the problem is to increase the number of state variables. Based on our findings, we believe that this type of increase would produce a dramatic increase in dynamic programming running time but would not significantly effect genetic algorithms running time. This assumption is supported by the "curse of dimensionality" inherent in dynamic programming (Dreyfus and Law, 1977). Further research is required to adequately compare the effectiveness of traditional search techniques (such as dynamic programming and gradient based non-linear programming) and genetic algorithms when applied to water resource management problems.

GENETIC ALGORITHM BASED MANAGEMENT TOOL

Three sets of final runs were made with the genetic algorithm guiding the search of operating strategies for the computer simulation based on the RGP. In the first set, the allotment was fixed at three acre-feet. Runs were made with and without the historical operating policy as a member of the initial population. Seeding the initial population with the historical operating policy allowed extensive search of the solution space near the current operating procedures. Beginning a run with an initial population generated entirely at random was intended to insure that the search was not biased by current operating procedures that may be good, but not optimal. Although the run seeded with the historical operating policy had much better strategies initially, both runs eventually produced strategies of roughly equivalent economic benefit. For the second set of runs, values of 2.5, 3.0 and 3.5 feet per acre were used for the allocation. These runs were made without the historical operating policy included in the initial populations. For the final set of runs, recreational benefits were increased by 2.5 times in order to make them more competitive with agricultural benefits. An allotment of 3.0 feet per acre was used. Runs with and without the historical operating strategy in the initial population were made.

All runs were conducted on IBM compatible personal computers with 486 processors. Final runs were carried out until roughly one million string evaluations had been made. These runs required approximately 14 hours of run time. One million trials represents an incredibly small portion of the 2^{832} possible operating strategies. The progress of these runs is shown in Figures 22 through 27. In these graphs, the best operating strategy found since the beginning of the search was plotted against the number of trials (or evaluations) completed. Figures 22 and 23 show the results from the runs with an allotment of 3 feet per acre, with and without the historical operating policy in the initial population. Figures 24 and 25 show the results of runs with allotments of 2.5 and 3.5 feet per acre, respectively. Figures 26 and 27 show the results of runs for increased recreation value with and without the historical operating policy in the initial population.

From these figures, it can be seen that the genetic algorithm found good strategies quite early in the search procedure. In general, as search progressed, the rate of improvement steadily decreased. Occasionally, the genetic algorithm made a rapid breakthrough to a region of the search space with increased performance, as shown in Figures 23 and 25. Eventually, the search stabilized and improvements to the best strategy were no longer found. Unlike other optimization techniques, it is not always obvious when genetic algorithm guided search is complete. Graphs like these can be used, however, to determine if future improvements are likely.

Note that for the runs whose initial populations included the historical operating policy, Figures 22 and 26, benefits were quite good from the very moment the search was initiated. These runs stabilized after a much smaller number of trials than required for searches whose

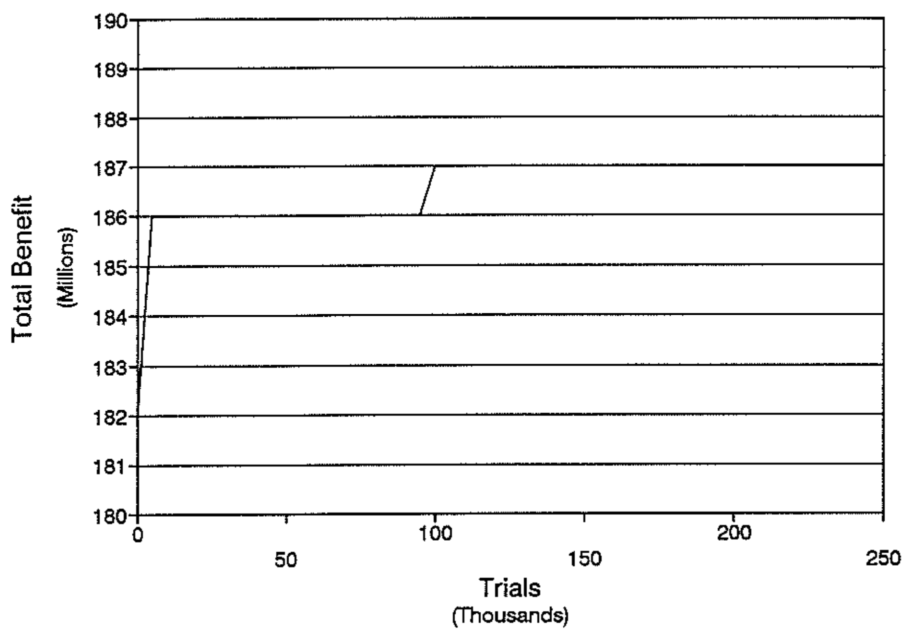

Fig. 22 Genetic Algorithm for 3.0 ft. Allotment W/H

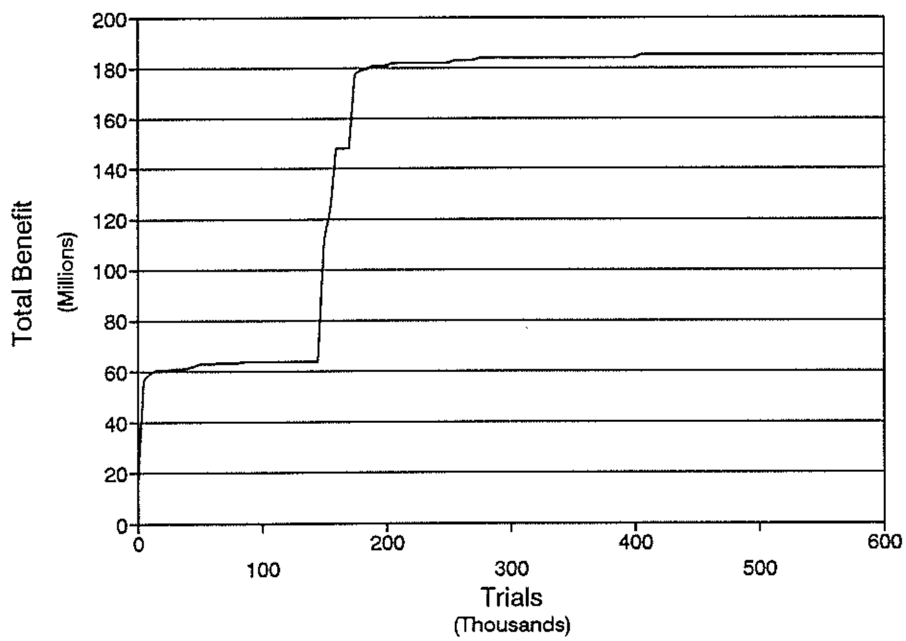

Fig. 23 Genetic Algorithm Performance for 3.0 ft. Allotment

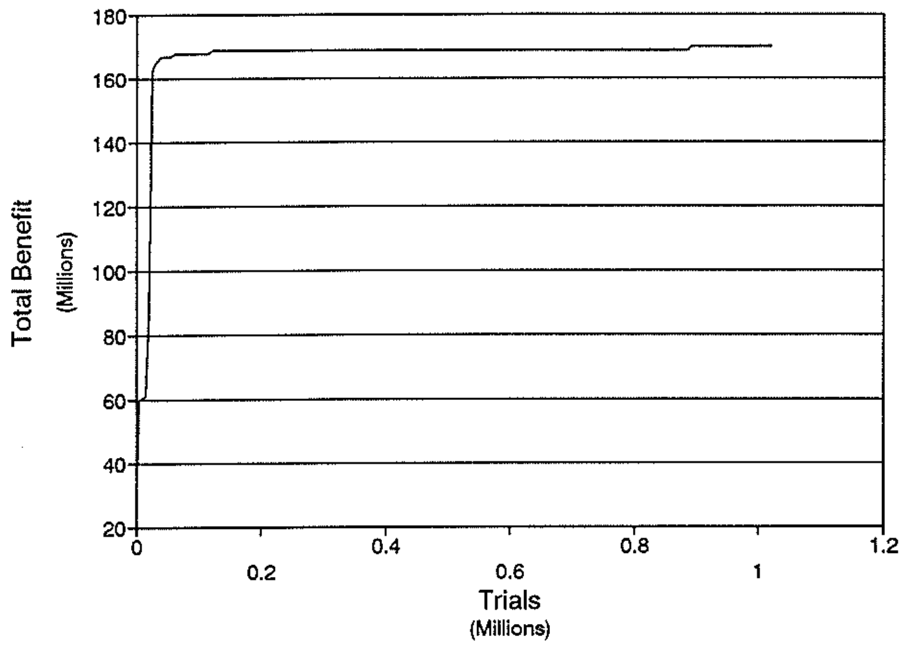

Fig. 24 Genetic Algorithm Performance for 2.5 ft. Allotment

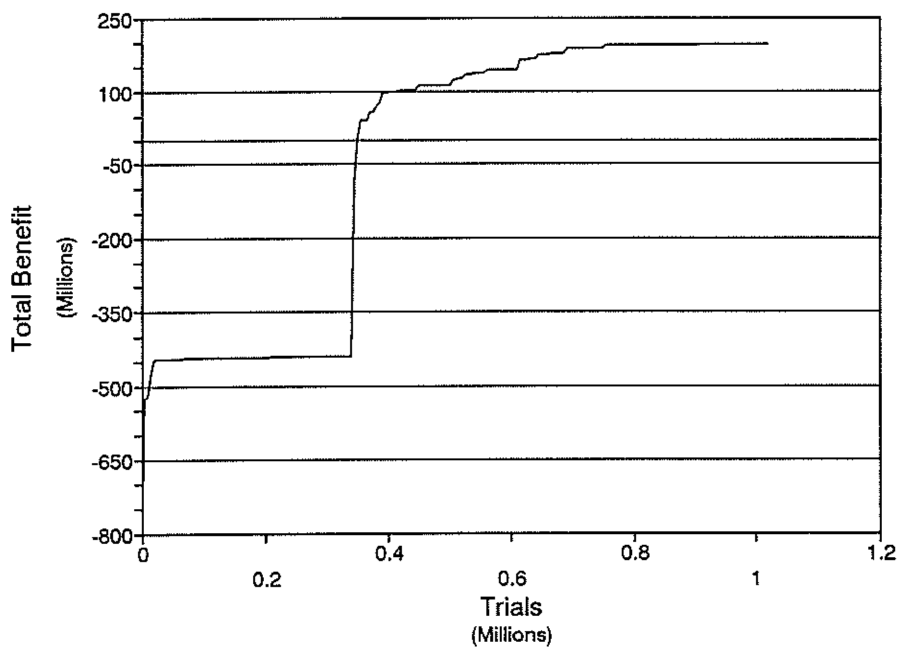

Fig. 25 Genetic Algorithm Performance for 3.5 ft. Allotment

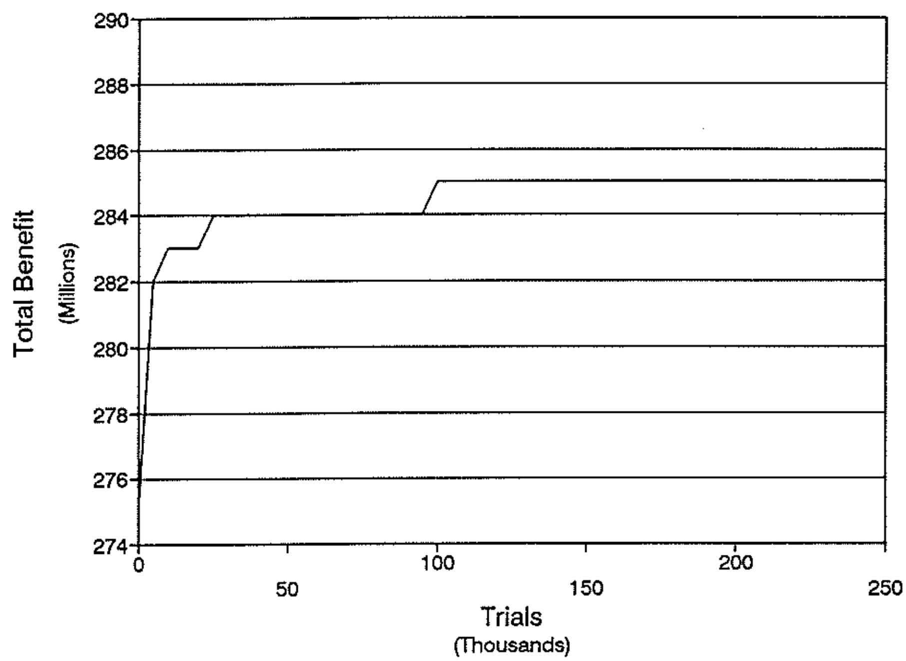

Fig. 26 Genetic Algorithm Performance for Increased Recreational Value W/H

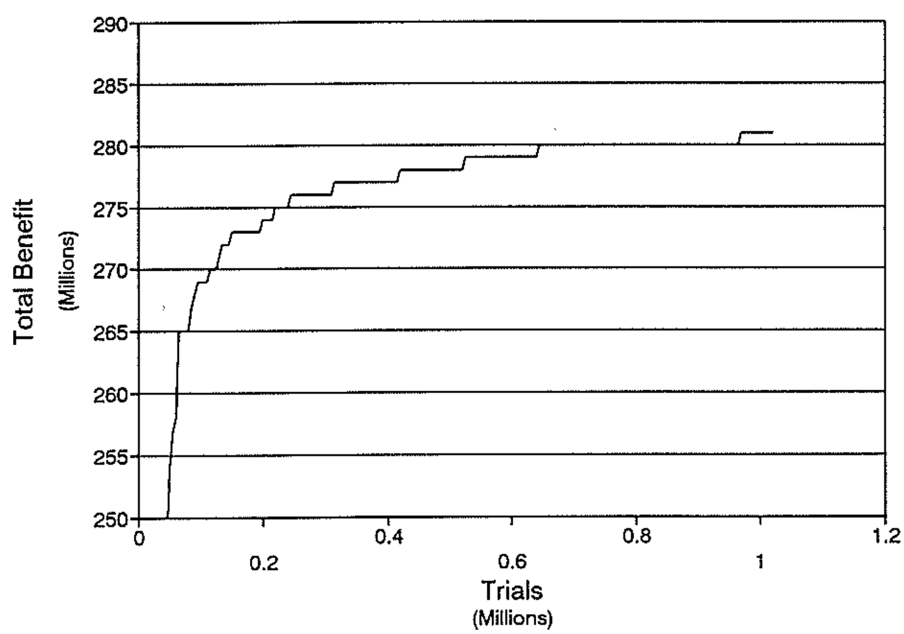

Fig. 27 Genetic Algorithm Performance for Increased Recreational Value

initial populations were generated entirely by random. Runs not seeded with the historical operating policy took longer to stabilize, but eventually reached values very comparable to those obtained by the runs with the historical policy (Figures 23 and 27).

Figures 28 through 30 show the total economic benefits for the three sets of genetic algorithm search runs. Figure 28 compares the total economic benefits of the historical operating policy ("HIST") and the best strategies found by the genetic algorithm search with a three foot per acre allocation. "GA W/H" represents the best strategy from the search with the historical operating policy in the initial population. The initial population of the run labeled "GA" did not include the historical operating policy. Both runs were able to produce strategies with improved performance relative to the historic operating policy. The historical operating policy produced a net benefit of $182.4 million, while the two genetic algorithm searches produced best strategies with values of $186.8 million and $185.0 million. Agricultural benefits for all three strategies were equivalent. The genetic algorithm searches increased benefits by improving hydroelectric and recreational benefits, as shown more clearly in Figures 31 and 32.

Figure 29 compares the best operating strategies found by genetic algorithm guided search for 2.5, 3.0, and 3.5 feet per acre allotments. All three runs were made with initial populations that were generated at random. Not surprisingly, total benefits increased with the size of the allotment due to increased agricultural benefits. This trend would continue until allotments become too large to allow operating strategies to avoid demand and end-of-year penalties. This set of runs demonstrates a procedure for optimizing the allocation even though it may not be efficient to do so with a single genetic algorithm search. Total benefits for the best strategies from these runs were $169.6 million, $185.0 million, and $195.8 million, for allotments of 2.5, 3.0, and 3.5 feet per acre, respectively.

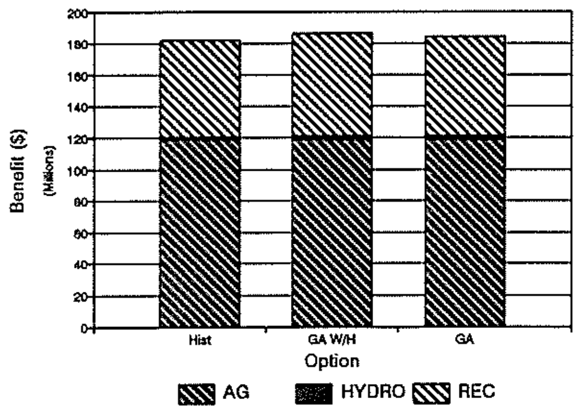

Fig. 28 Total Economic Benefits of Operating Strategies

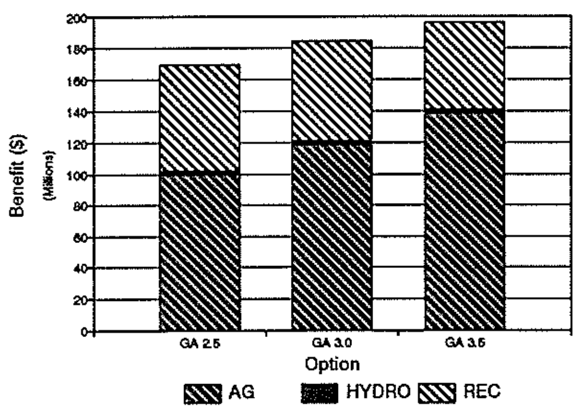

Fig. 29 Total Economic Benefits of Strategies from GA for Various Allotments

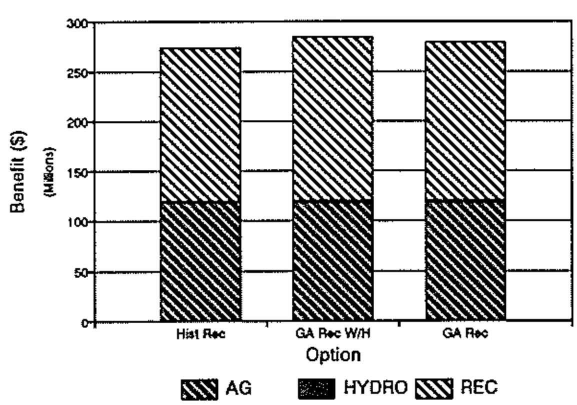

Fig. 30 Total Economic Benefits of Strategies for Increased Recreational Value

Figure 30 evaluates the consequences of increasing the value of recreation by 2.5 times. Benefits for the historical operating policy and two genetic algorithm runs (with and without the historical policy in the initial population) are shown. These runs were made for an allotment of three feet per acre. Because recreation was more valuable, total benefits were increased. The value of agricultural benefits were unaffected, however. A competition between agricultural and recreational uses never developed because of the demand penalties for failing to meet agricultural demand. The historical operating policy produced total benefits of $275.2 million. This was increased to $285.4 million for the best strategy for genetic algorithm search with the historical policy in the initial population and $280.6 million without.

Figure 31 shows hydroelectric benefits for the historical operating policy and best strategies of the various runs. From the three series on the left of the graph, it can be seen that the genetic algorithm increased hydroelectric benefits by more than 25% over the historical operation in the first set of runs. Hydroelectric benefits were relatively equal for the three different allotments of the second set of runs. Benefits were slightly reduced as recreation was given a higher value in the last set of runs.

Figure 32 shows the recreational benefits associated with operating polices from historical operation and the genetic algorithm searches. Recreation was slightly increased from the historical value for the first set of runs. Not surprisingly, in the second set of runs, recreational benefits decreased as the allotment increased. In the third set, increased value of recreation caused a large increase in recreational benefits. The improvements generated by the genetic algorithm searches were larger in magnitude, but not significantly different in terms of percent change from the historical value.

For the first set of genetic algorithm based searches, additional graphs were made in

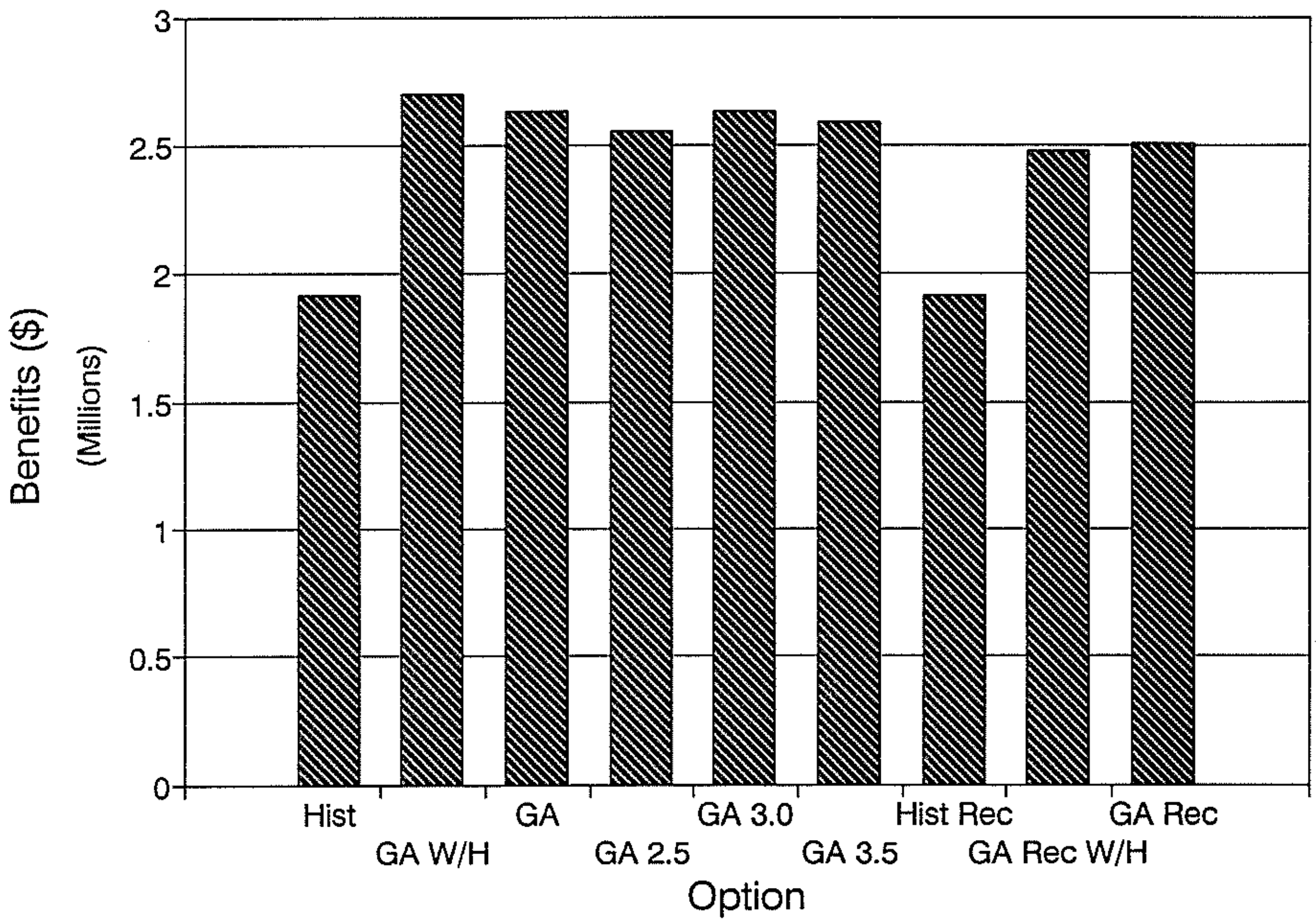

Fig. 31 Hydroelectric Benefits of Operating Strategies

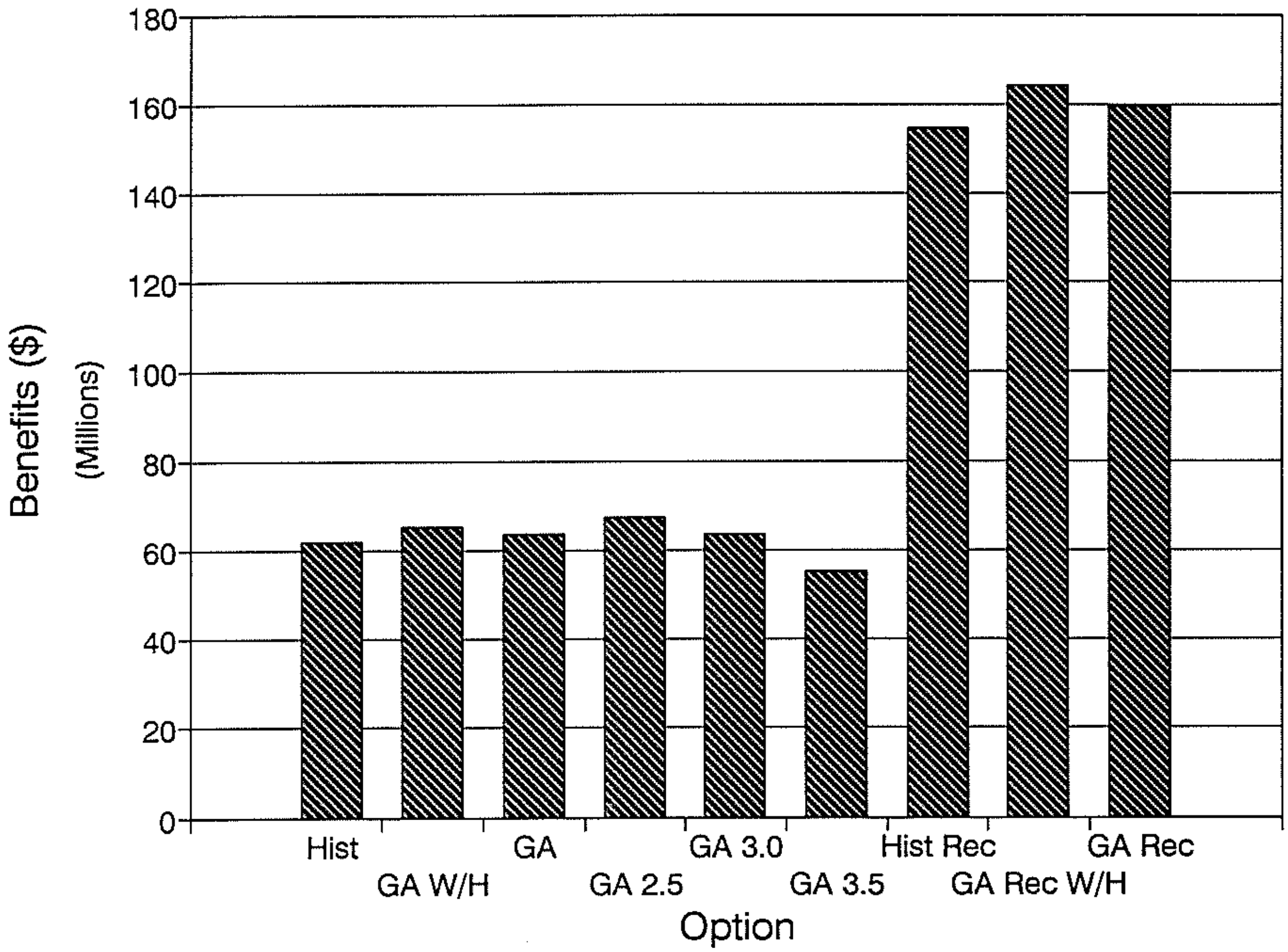

Fig. 32 Recreational Benefits for Operating Strategies

order to analyze the difference between historical operation and that suggested by the genetic algorithm. Figures 33 through 35 show the behavior of Elephant Butte Reservoir for historical operation and the best strategies suggested by the genetic algorithm guided searches, with and without the historical policy in the initial population. From these figure, it can be seen that the policies found by the genetic algorithm release more water than the historical policy. The magnitude of releases seem to vary more from week to week. Both these factors may contribute to increased hydroelectric benefits. More release volume results in more hydroelectric generation. Making larger releases also results in greater turbine efficiency.

Figures 36 through 38 show the behavior of Caballo Reservoir. Releases suggested by the genetic algorithm searches again are larger in magnitude than those employed by the historical operating policy. In general, however, the releases from Caballo are much closer to the historical values. The volume of Caballo Reservoir is maintained at a much higher value for the strategies suggested by the genetic algorithm searches. This seems to be the driving force behind the increased recreational benefits of these strategies. Evaporation losses are also greatly increased. The genetic algorithm search seems to indicate that the value of water lost to evaporation is more than offset by increased recreation benefits when Caballo volume is maintained at a higher value. These results, or course, are based on our model of the RGP system. Any contradiction of previous studies or operating policies could be due to either the model's inability to accurately simulate response of the RGP or the limitations of a single year optimization period. In either case, our results demonstrate the ability of a genetic algorithm to find regions of higher performance when operating a complex model.

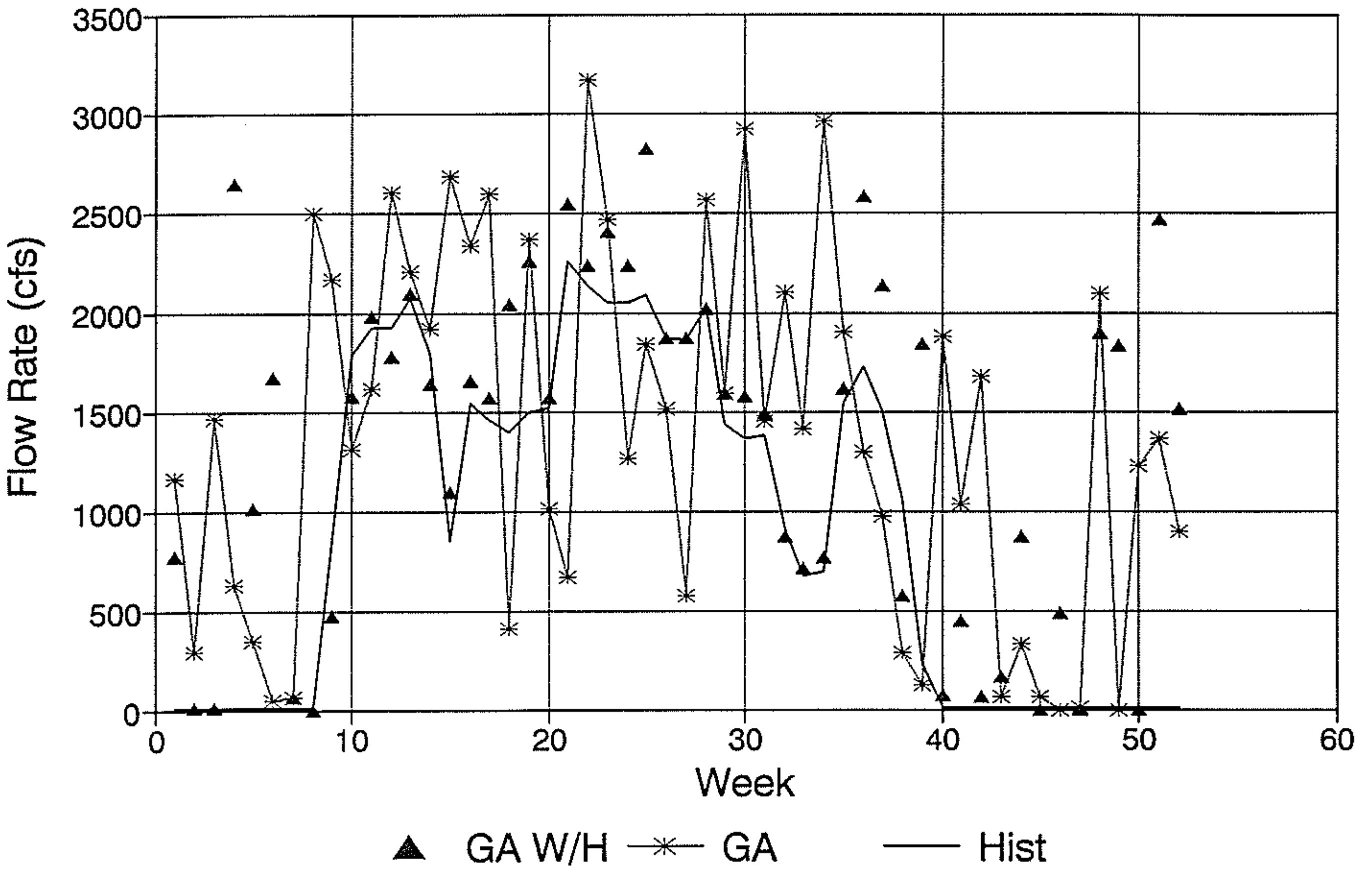

Fig. 33 Releases from Elephant Butte Reservoir

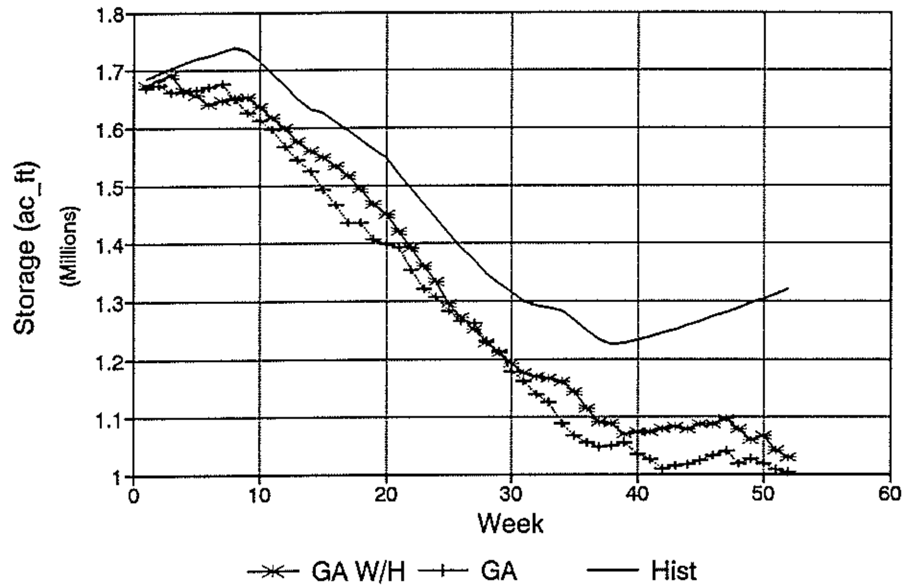

Fig. 34 Elephant Butte Reservoir Storage Volume

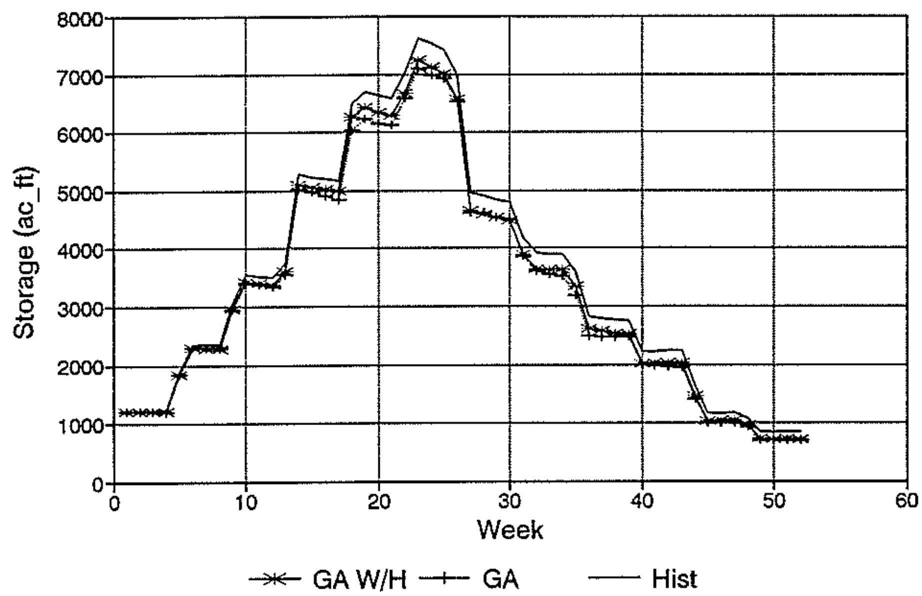

Fig. 35 Evaporation Losses at Elephant Butte Reservoir

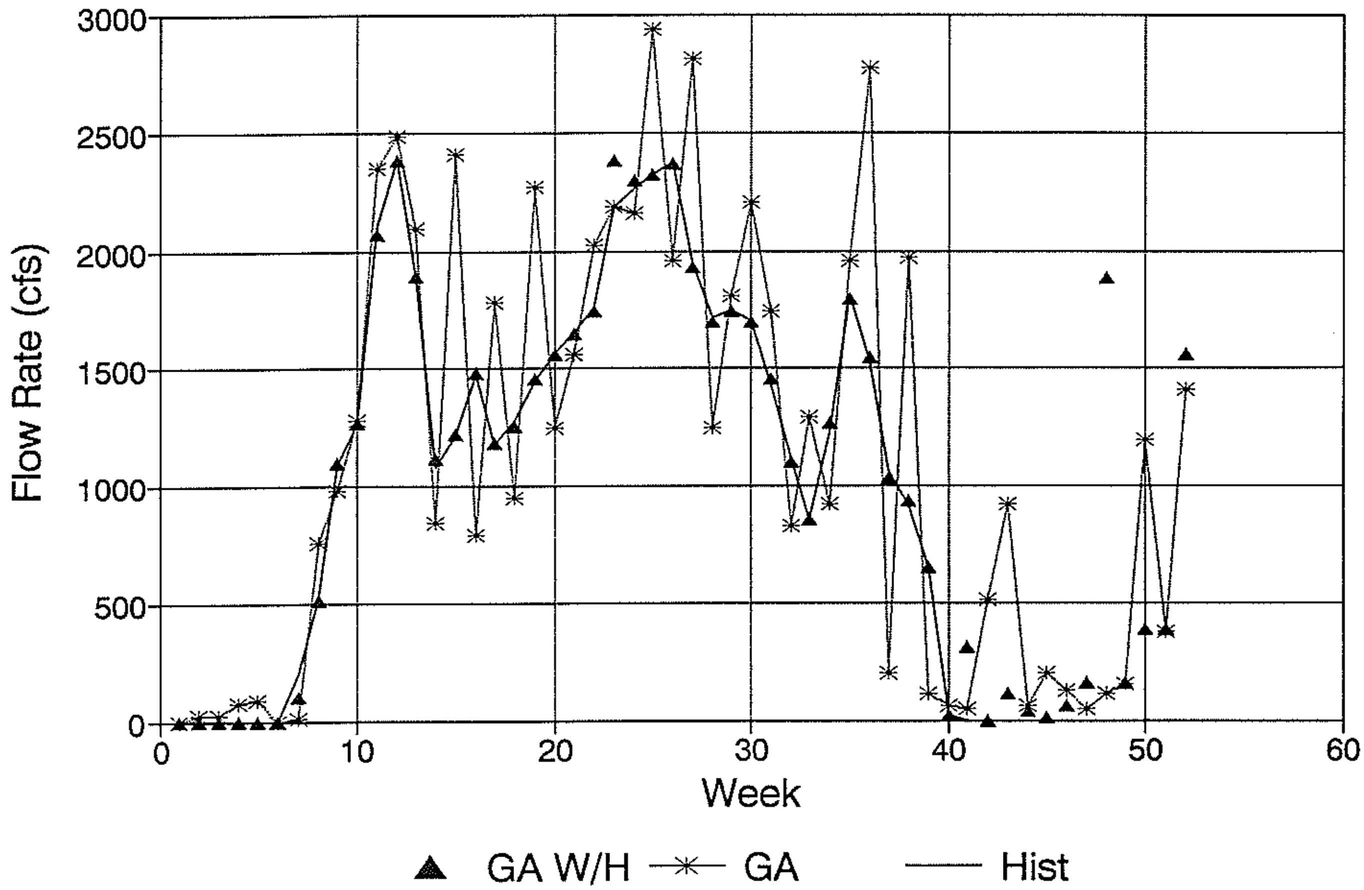

Fig. 36 Releases From Caballo Reservoir

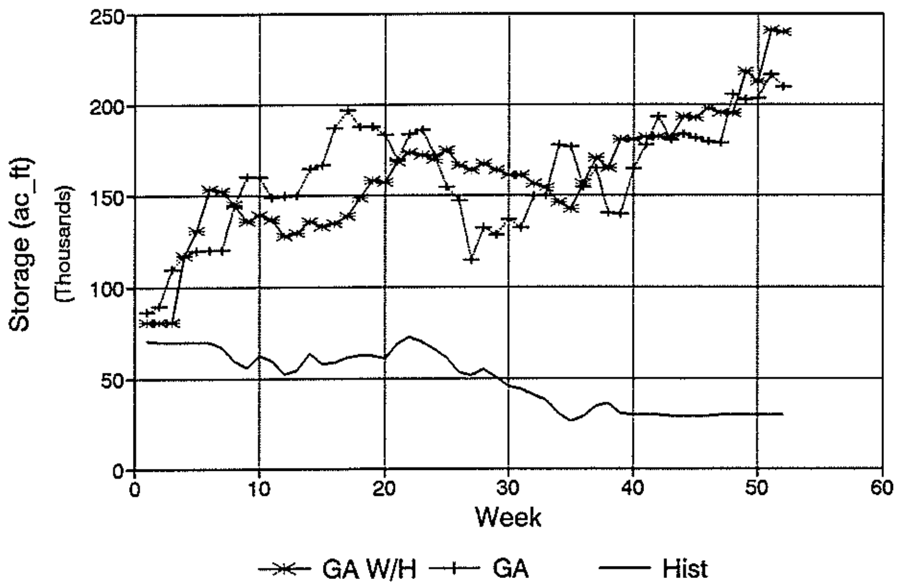

Fig. 37 Caballo Reservoir Storage Volume

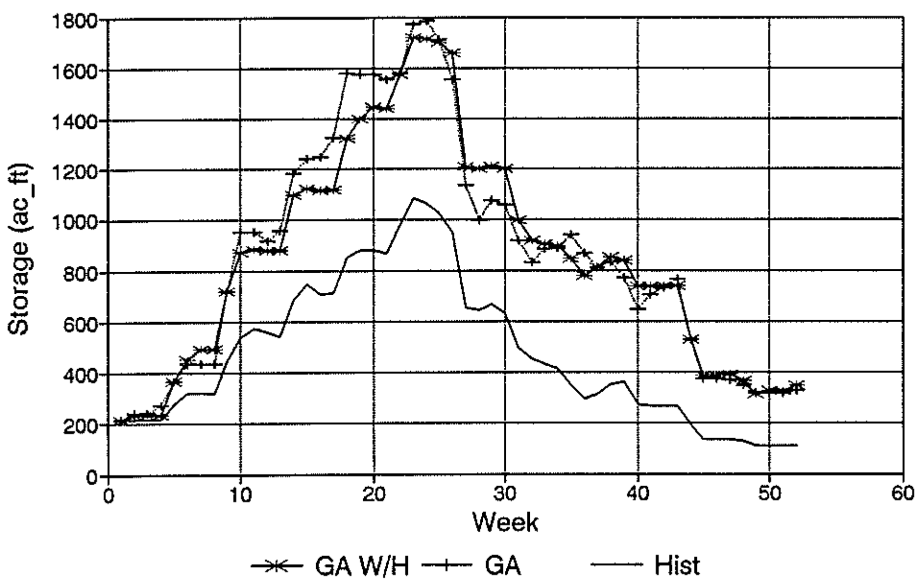

Fig. 38 Evaporation Losses for Caballo Reservoir

CONCLUSIONS

This research investigated the potential of genetic algorithms to optimize the operation of complex models of water resources systems. Such models pose a significant challenge to conventional optimization approaches. As a result of this research, we have reached the following conclusions:

1. Genetic algorithms are capable of optimizing water resources system models of greater complexity than current techniques allow. For the simple exercise performed here, genetic algorithm search performance appeared better than dynamic programming.

2. Genetic algorithms do not always find the optimal solution nor is it always obvious when improvement has stopped. Nevertheless, for many applications, finding near optimal solutions or solutions that represent improvements on current practice are sufficient.

3. Genetic algorithms appear capable of optimizing complex models of water resources systems. In this case study, they were able to find improved operating strategies for a representative model of the RGP.

4. As with all optimization techniques, the results of genetic algorithm guided search are only as good as the model of the system used in the optimization process. The optimization capabilities of genetic algorithms will help justify the effort and cost to develop accurate and complex system simulations.

5. There is room for improvement in the application of genetic algorithms to realistic water resources problems. Topics for future research include problem formulation and genetic algorithm operators designed to reduce the generation of infeasible solutions.

6. Further research is required to adequately compare the effectiveness of traditional search techniques (such as dynamic programming and gradient based non-linear programming) and genetic algortihms when applied to water resources problems.

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