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Decision support model for operation of multi-purpose water resources systems

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ABSTRACT

Models to search for optimal operation rules of complex water resources systems generally represent the physical system in a fixed static form, being difficult to incorporate changes in water offer, water demand and system structure. This paper presents a decision support procedure that integrates continuous simulation, artificial neural networks, and optimization to produce decision rules in watershed management for multiple purpose complex water resources systems. The system uses physical indexes to evaluate the compliance of targets for the different purposes of the system, such as occurrence of failure (frequency), resilience (duration and capacity of recovery of a state of failure) and vulnerability (severity or magnitude of the failure). It also introduces a global indicator of the behavior of the system, which combines, with user selected weights, the previous indexes in a measure of global effectiveness. The methodology was applied to the San Juan River Basin, Argentina, and results show conclusively the usefulness of simulation in the study of alternatives of water resources systems with multiple uses and the feasibility of using neural networks to encapsulate the behavior of simulation models. The encapsulated model and parametric operation rules can be included in a dynamic optimization process to search for optimal operation policies.

RÉSUMÉ

Keywords: Simulation, planning, multi-purpose water resources systems, decision support systems, artificial neural networks, optimization, reservoirs operation, watershed management.

1 Introduction

Numerous studies address the problem of defining optimum operation rules for reservoir systems with multiple purposes. (Nalbantis and Koutsoyiannis, 1997; Belaineh *et al.*, 1999; Lund and Guzmán, 1999; Morel-Seytoux, 1999; Sanchez-Quispe, 1999). However, most studies use fixed management rules in the search of solutions and cannot adapt to changes that the system undergoes.

The uncertainty of the availability and demands of water for different uses is an additional degree of difficulty in operational decisions. Since future events are not known with certainty, the user needs to evaluate the risk of making certain decisions. To make an exhaustive analysis of operation alternatives under uncertainty, requires computation of outcome probabilities associated to each alternative, for every time horizon. A reliable estimation of these probabilities needs multiple simulation runs and the computational time for a large number of alternatives, makes this problem unapproachable with conventional methods. For this reason, the analysis of alternatives based on risk is solved by trial and error, without carrying out a true optimization process.

This paper presents a decision support system that offers the manager a dynamic tool to customize the problem and to search for an optimal management policy. The procedure increases the capacity to search for solutions by combining simulation and

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optimization. The model allows a trial and error search of alternatives based on risk or performs an exhaustive analysis of alternatives based on certainty.

The method is a combination of simulation of continuous processes, artificial neural networks (ANNs) and optimization techniques. The system uses operation rules and restrictions expressed parametrically, calculates measures of effectiveness for different uses of water and combines them using relative weights. This approach generates a novel and effective mathematical model that uses simulation and optimization simultaneously. As a result, it is possible to construct a dynamic objective function that adapts to changing requirements of the users, and finds good management practices, without modifying the simulation model. The mathematical model can be easily adapted to account for system dynamics, such as, changes in water offer and demand, changes in water use priorities and modifications of the relative importance of behavior indexes for each use.

The use of ANN techniques in water resources is relatively new and has been reported by French *et al.* (1992), Karunanithi *et al.* (1994), Hatta *et al.* (1996), Raman and Sunilkumar (1995), Zealand *et al.* (1999), Zhu and Fujita (1994), Hsu *et al.* (1995) and Dölling and Varas (2001), among others. However to our knowledge, the integration of simulation, ANN models, optimization of water resources systems, parametric representation of parameters and production rules has not been reported.

2 Search process of the optimal operation alternative

The decision support method implemented by SARH-2000 (Dölling, 2001), uses simulation and optimization to search for an optimal solution within a space of feasible states that comply with the transition rules between states. The solution of the problem can be the final state or the trajectory to get to the solution (Gerez and Grijalva, 1988). Figure 1 shows a block diagram with the structure of the search process.

The state space in a simulation problem is usually discontinuous and finding the optimal solution is not always possible. On the other hand, the state space in optimization models is defined by continuous and derivable functions. This fact constitutes a significant conceptual difference in the search for solutions in both approaches. Nonetheless, they can be combined in a single search method, when simulation results are encapsulated using an ANN. Since this model is continuous and derivable it can be introduced in a nonlinear optimization scheme.

2.1 Simulation

To simulate the behavior of a water resource system, it is necessary to formulate an operational model of the physical system and to define the elements, the relations between elements and the inputs. The process needs the hydrological data base to characterize the problem. This information can also be used if necessary, to formulate a stream-flow forecasting model. Additional data for the simulation model are the attributes and relationships between objects and variables, the interaction between variables, the measures of effectiveness of the behavior of the system, the set of operation rules that define the restrictions of the space of feasible states and the operation rules of the control elements of the system (reservoirs, gates, pumps).

The simulation analysis evaluates the performance of an operation alternative using a series of historic or synthetic monthly

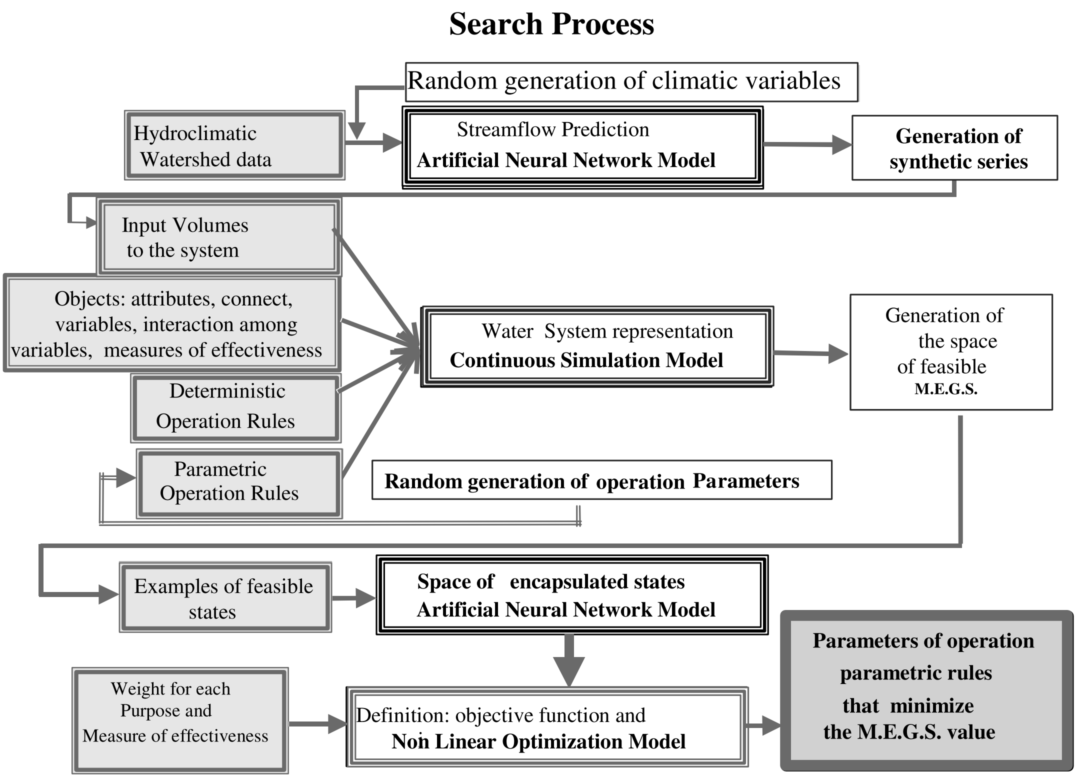


Figure 1 Process to search for solutions.

flow volumes for the period of study. The decision support model compares system behavior under different operation rules and helps the manager to select those rules that behave better or to formulate operation rules at the planning level. In this study, operation policies were defined using physical output measures, such as the frequency or probability of failure, the probability of recovery from states of failure or resiliency and the magnitude of deficits or vulnerability for each water use (Loucks and Sigvaldason, 1982; Azevedo *et al.*, 2000; Cai *et al.*, 2002).

The first step in the simulation process is to define the search space of the control elements by setting upper and lower limits for the parameters. Next, random values of parameters are generated to build a space of operation alternatives large enough to obtain a complete representation of the response surface.

2.2 *Encapsulation of simulation results*

Since simulation does not produce an optimal alternative and the simulation model is too complex to include in the objective function of an optimization model, we propose to encapsulate simulation results using an ANN model, capable of reproducing a set of results of the behavior indices as a function of the input variables which characterize a given alternative. Some efforts to use encapsulation on other fields have been reported (Dibike *et al.*, 1999)

An ANN is a mathematical model which has a highly connected structure similar to brain cells. It consists of a number of neurons arranged in different layers, an input layer, an output layer and one or more hidden layers. The input neurons receive and process the input signals and send an output signal to other neurons in the network. Each neuron can be connected to the other neurons and has an activation function and a threshold function, which can be linear or nonlinear continuous functions. The signal passing through a neuron is transformed by weights which modify the functions and thus the output signal that reaches the following neuron. Modifying the weights for all neurons in the network changes the output. Once the architecture of the network is defined, weights are calculated so as to represent the desired output through a learning process where the ANN is trained to obtain the expected results. Information available is used to define a learning or training data set and a validation data set (Rumelhart *et al.*, 1994).

2.3 *Optimization*

The optimization model includes an objective function that minimizes the global effectiveness of the system (MEGS) which is a linear combination of behavior indices of failure calculated for every water use, subject to restrictions imposed on parameters by the operation rules. This global indicator is defined as follows:

$$MEGS = \sum_{i=1}^{5} b(i) * \sum_{j=1}^{3} \frac{p(i,j) * I(i,j)}{I_{\max}(i,j)} \tag{1}$$

where

i = type of water use of the system: (1) irrigation; (2) energy; (3) flood control ; (4) ponding Control; (5) recreation,

j = behavior index: (1) occurrence of failure; (2) complement of resilience; (3) vulnerability,

$b(i)$ = relative importance assigned to water use (i) by the user. (policy decision),

$p(i,j)$ = relative importance assigned by the user to the behavior index (j) of water use (i)

$I(i,j)$ = value of the behavior index (j) of water use (i)

$I_{\max}(i,j)$ = maximum Value (reached in the 3.500 simulations) of the behavior index (j) of water use (i), used for scaling purposes.

The behavior indices measure the performance of the system with respect to water deficits and the ability to recover from states of failure. Occurrence of failure is equal to the probability of having a water shortage for a certain use, and it was calculated as the ratio of the number of failures and the total period in the simulation. Vulnerability was defined as the magnitude of the largest deficit or failure for a particular use of water in the simulation period. Resilience expresses the capacity of the system to recover from a state of failure. The objective function includes the complement of resilience which is the probability that the system does not recover from a state of failure. It is calculated as the probability that the system is in state of failure in the following period given that it is currently in a state of failure.

Constraints of the optimization model are of two types. Some are related to physical characteristics of the proposed or existing structures, such as maximum storage volumes of reservoirs, dead or minimum storages of reservoirs, maximum discharge of the reservoirs, maximum capacity of pumping wells, capacity of water distribution channels. Other constraints are operational and these are defined by the range of feasible states of the control elements, such as water demands in each period for different uses, energy generation, size of flooded areas, pumped volumes, water volumes derived for irrigation, drinking water demands.

3 Application to the San Juan River Basin

We applied the proposed model to analyze management alternatives for the San Juan River Basin in Argentina (Dölling, 2001). Water resources demands include potable and industrial water, irrigation, hydroelectricity, flood control, recreation and surface ponding control (Figs 2 and 3). The water resources system includes three reservoirs, three hydroelectric power plants, a diversion dam, three irrigation areas, San Juan potable water, two aquifers and two pumping systems to control aquifer water tables.

4 Encapsulating the simulation results in an artificial neural network

Dölling and Varas (2000) formulated a continuous simulation model to represent the San Juan River Basin system using Extend© (1990) (Fig. 4). This model calculates behavior indexes for each month for five water demands of the system (irrigation, hydropower, flood control, ponding control and recreation).

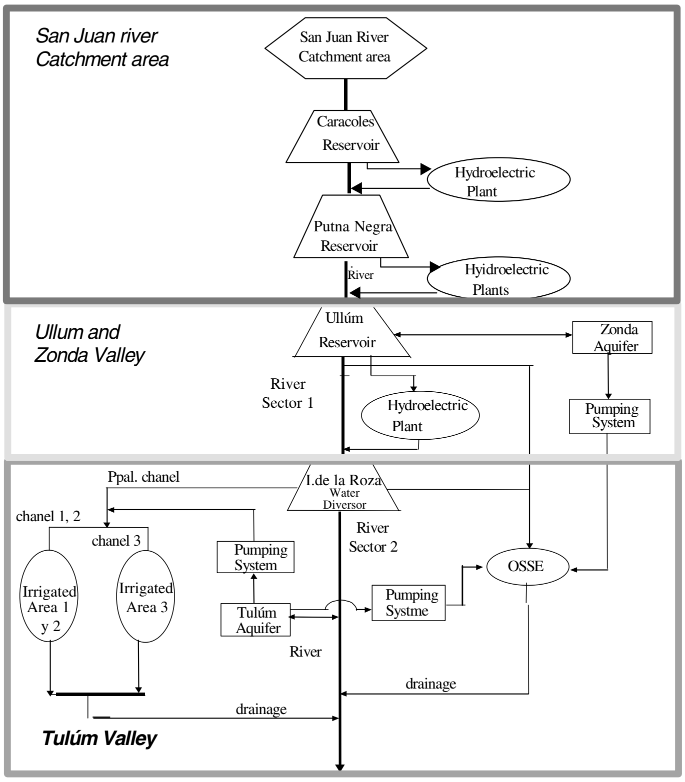


Figure 2 San Juan River Basin diagram.

The algorithm to calculate the behavior index for each use and month is summarized in Fig. 5.

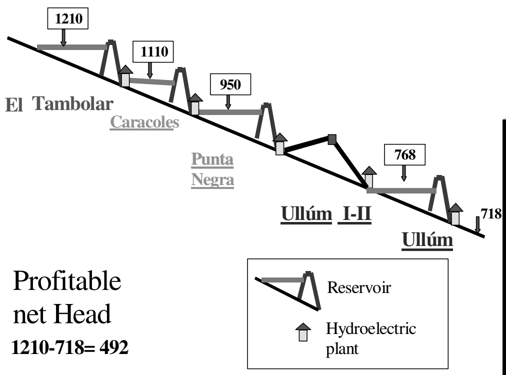
Overall performance of the system from the beginning of the simulation period to the current month was measured by the probability of having a failure to provide the required water for each use (occurrence of failure), the capacity of the system to recover from a state of failure (resilience) and the maximum deficit (vulnerability). The algorithm to calculate the measures of performance of the system for each water use is presented in Fig. 6.

The simulation model produces the indices of behavior for each month and calculates for each period the behavior index for occurrence of failure, vulnerability and the complement of resilience for each water use. Thus a matrix of behavior indices for each water use and performance measure was obtained for each period. A global measure of system behavior (MEGS) for the current month is calculated using Eq. (1) with relative weights provided by the user.

The model simulated 3.500 randomly generated management scenarios, to represent the range of the operational parameters of the five control elements. These controls represent the water volumes released by the reservoirs (Caracoles, Punta Negra and Ullum), the water derived for irrigation at Partidor San Emiliano and the volume of water pumped by a group of wells in the Tulúm valley. The operation scenarios were defined by expressing the operation controls parametrically. The simulation runs give measures of effectiveness of the system (occurrence of failure, complement of resilience and vulnerability) for each purpose and management scenario, following the algorithms of Figs 5 and 6. Results were used to train and validate a neural network capable of encapsulating the behavior of the system under different situations.

It was found that the ANN captures the structure of the simulation model and predicts accurately the 15 behavior indexes, that is to say, the index of occurrence of failure, resilience and vulnerability for each water use. We used the SNNS software (Zell *et al.*, 1995) to train, validate and test the neural network. We obtained a good predictive behavior using a feed-forward 5–10–10–15 ANN (5 input neurons, 2 layers of 10 hidden neurons and 15 output neurons), trained by back-propagation momentum (Fig. 7). We initialized the network with random values between -1 and 1 and studied the convergence of the back-propagation method for different rates of learning and different coefficients of momentum. Finally, we adopted values equal to 0.5 and 0.2 for the mentioned parameters, respectively.

We used 3.500 input–output duples: 2.000 for training 1.000 for validation and 500 for testing the network. Each duple consisted of 5 input variables and 15 output variables. The 5 input variables ($X_1, \ldots, X_5$) are the parameters of the operation rules



Name	Reservoir capacity (Hm3)	Power (Kw)	Generation/year (millons Kwh)
ElTambolar	600	70000	330
Caracoles	575	123400	545
Punta Negra	500	76000	325
Ullum I-II		43000	235
Quebrada delúm	440	47000	172
Totales	**2115**	**359400**	**1607**

Item	Value	Unit
Catchment Area	20,000	Km^2
San Juan River mean flow	70	m^3/seg
Total Reservoir Capacity	1,500	Hm^3
Nominal Power (all plants)	24640	Kva
Distribution Capacity	0 82.5	m^3/seg
Total irrigation area	70,000	Has
Aquifer capacity	68,000	Hm^3
Pumping system capacity	25	m^3/seg

Figure 3 Physical characteristics of San Juan River system.

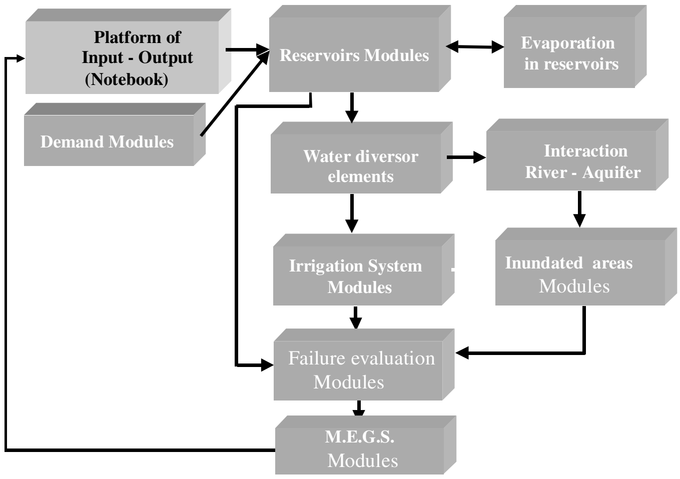


Figure 4 Modular structure of simulation model.

for the control elements of the system and the 15 output variables are the behavior indexes for each water use.

The reservoir parameters of Caracoles (X_2), Punta Negra (X_4) and Ullúm (X_3) have a range [-0.3 to $+0.3$]. A zero value (0) indicates that the reservoir satisfies exactly the volume of water demanded by the system. Positive values (+) represent the proportion of water that the reservoir discharges in excess of total demand. Negative values correspond to situations in which the reservoir delivers less water than the volume demanded.

The water discharged by Ullúm reservoir flows to Ignacio de la Roza Dike, which can discharge water to the main irrigation channel or to the river. The water derived to the main channel goes to the Partidor San Emiliano and is distributed to the three irrigation channels or discharged to the river if necessary.

The operation rules for water distribution were parametrized for the combined operation of Ignacio de la Roza Dike–Partidor San Emiliano for situations when the water discharged by Ullum reservoir exceeds the irrigation water requirement. When the volume of water discharged by Ullum is equal or less than the volume required for irrigation, the combined Dike–Partidor discharges all available water to irrigation. The parameter of the combined Dike–Partidor (X_1) has a range of [-0.5 to $+0.5$] and represents the volume of water derived into the river. A null value implies that the total volume of water exceeding the irrigation requirement is derived to the river. Positive values represent situations in

BEHAVIOR INDICES

Irrigation (IR)

IR = Volume of Irrigation Demand – Volume of available water for irrigation

Energy (IE)

Variable definition

Var1 = Volume of water demand for irrigation
Var2 = Volume demand of Caracoles Reservoir
Var3 = Volume delivered by Ullum Reservoir
Var4 = Volume delivered by Caracoles Reservoir
Var5 = Volume of water demand of Punta Negra Reservoir
Var6 = Volume of water delivered by Punta Negra Reservoir

If (Var1-Var3 < 0 AND Var2-Var4 < 0) then Result1 = 0
If (Var1-Var3 < 0 AND Var2-Var4 >= 0) then Result1 = Var2-Var4
If (Var1-Var3 >= 0 AND Var2-Var4 < 0) then Result1 = Var1-Var3
If (Var1-Var3 >= 0 AND Var2-Var4 >= 0) then Result1 = (Var1-Var3) + (Var2-Var4)
If (Var5-Var6 < 0) then Result2 = 0
If (Var5-Var6 >= 0) then Result2 = Var5-Var6

IE = Result1 + Result2

Flood Control (IFC)

IFC = Volume delivered to the River – Maximum admissible volume

Ponding Control (IP)

IP = Flooded surface – Maximum admissible flooded surface

Recreation (IREC)

Var1 = Ullum Reservoir water level

If(Month > 9 OR Month < 4 AND Var1 < 765) then IREC = 765 – Var1
Else IREC = 0

Figure 5 Definition of behavior indices.

PERFORMANCE INDICES

Step 1

(a) Calculate the state of the system (use i, time t)
Failure state (i,t) = 1 if failure
Failure state (i,t) = 0 if success
(b) Calculate number of failures between time t = 0 and time t = N (actual or current time)
nfailures(i, N) = sum(Failures states (i, t) for t = 0 to N)

(c) Calculate probability that a failure state continues for next period

P(X, i) = Prob (M | F) = (sum(state (failure(i)$_t$ | Failure(i)$_{t-1}$) for time t = 0 to time t = N))/ n failures(i, N)

Step 2

(d) Calculate successes
Success (i, t) = 1 if target is met
Success (i, t) = 0 if target is not fulfilled
(e) Calculate the number of success states between time t = 0 and time t = N (actual or current time)
nsuccess (i, t) = n failures(i, N) - N
(f) Calculate probability that a success state continues for next period

P(Y, i) = Prob (M | S) = (sum((success(i,t) | success(i,t-1) for time t = 0 to time t = N))/ nsuccess(i, N)

Step 3

(g) Calculates vulnerability (i, t) as the maximum magnitude of deficit (i, t) for time t = 0 to time t = N
(h) Calculate the probability or occurrence of failure of period N

P(Z, i) = n failures(i, N) / N

(i) Calculate the complement of Resilience (CR)

CR(i) = 1- [P(X,i)*P(Z,i)/(P(X,i)*P(Z,i) + P(Y,i)*(1-P(Z,i))]

Figure 6 Algorithm to calculate performance indices.

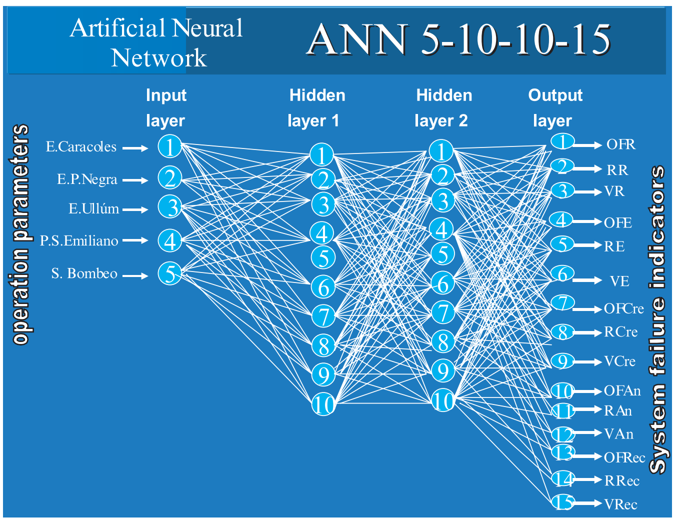


Figure 7 ANN to encapsulate simulation model (notation in Table 1).

which more water is derived to the river causing deficits in irrigation. Negative values represent situations in which the irrigation sector receives more water than the volume demanded.

Water table depths in the Zonda and Túlum aquifers are very shallow and ponding control is urgently needed. The parameter of the pumping system (X_5) varies between 0 and 100. A zero value indicates that no ponding control is accomplished in the valley, that is, the pumping system is inactive. A value (100) implies that 100% ponding control is required in the valley. In this case, the valley has a maximum of 1000 Has with a water table depth less than 1 m.

The 15 output variables of the model are the values of the three behavior indexes for each of the five water uses. All values in the duples were scaled to -0.7 and $+0.7$ to homogenize the magnitudes of the different variables. The sigmoid activation function was used at output of each neuron, to be able to extrapolate output values larger than the ones used in the training process of the network. The value of the behavior index (j) for each water use (i) included in the objective function is estimated using the ANN model as a function of the input control variables $(X_1, \ldots, X_5)$.

The ANN model can be summarized in the following set of equations:

Output of input layer: X_i for $i = 1, \ldots, 5$

Output of hidden layer 1:

$$y_j = \left(1 + \exp\left(-\left(a_{0j} + \sum_{i=1}^{5} a_{ij} X_i\right)\right)\right)^{-1} \qquad j = 1, \ldots, 10 \tag{2}$$

Output of hidden layer 2:

$$y_k = \left(1 + \exp\left(-\left(b_{0k} + \sum_{j=1}^{10} b_{jk} y_j\right)\right)\right)^{-1}$$
$$k = 1, \ldots, 10 \qquad (3)$$

Result of output layer:

$$y_m = I_m = \left(1 + \exp\left(-\left(c_{0m} + \sum_{k=1}^{10} c_{km} y_k\right)\right)\right)^{-1}$$
$$m = 1, \ldots, 15 \qquad (4)$$

The sum of square errors (SSE) in the test pattern indicates that the network is capable of generalization after 50.000 training cycles. In general, the ANN and the simulation model give similar values for the behavior indexes, as shown by Figs 8 and 9. The ANN model for the 500 test examples gave acceptable values of the absolute scaled error. The maximum average value of this error is 6.18% with a standard deviation of 8.12% (Table 1).

The global effectiveness index (MEGS) represents the overall behavior of the system. The optimization model searches for a feasible administration policy that produces the smallest value of MEGS in a hyperspace of five dimensions, each corresponding to one of the operation parameters that define the management policies of the system. Behavior indexes for different purposes were scaled between 0 and 1 to combine them.

Figures 8 and 9 and Table 2 compare MEGS values calculated with the ANN model and the ones calculated with the Extend© simulation model for the 3.500 examples for different weight configurations. As shown in the diagrams, the ANN model captures the global behavior of the system acceptably, although there is a tendency to underestimate the MEGS parameter for low values and overestimate for high values for this set of priorities. Other configurations of relative weights and effectiveness measures gave similar values of error and dispersion.

Table 2 shows that deviations and errors are small and adequate to the purposes of the method, so the ANN model can be used to search for small MEGS values using nonlinear optimization.

Once the ANN model was trained and validated, the model was introduced as part of the mathematical structure of the objective function, or equation to calculate the MEGS index. The inclusion of a complex simulation model in the objective function is impossible, due to the large amount of calculations. However, the mathematical representation of the ANN that encapsulates simulation results is simple and can be included in the objective

Purpose	weight	Effectiveness Measure	weight
Irrigation	0.5	Vulnerability	1
		Failure frecuency	0
		Resilency	0
Energy	0.3	Vulnerability	0.1
		Failure frecuency	0.4
		Resilency	0.5
Aquifer control	0.1	Vulnerability	0
		Failure frecuency	0.1
		Resilency	0.9
Flood control	0.05	Vulnerability	0.5
		Failure frecuency	0.1
		Resilency	0.4
Recreation	0.05	Vulnerability	0
		Failure frecuency	0.5
		Resilency	0.5

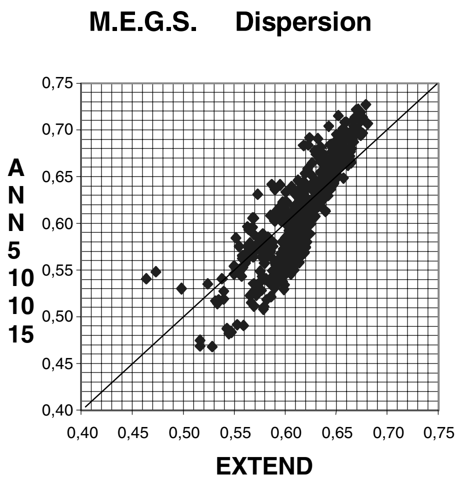


Figure 8 Comparison of MEGS calculated with the simulation model and the ANN model (Example 1).

Purpose	weight	Effectiveness Measure	weight
Irrigation	0.5	Vulnerability	1
		Failure frecuency	0
		Resilency	0
Energy	0.3	Vulnerability	0.1
		Failure frecuency	0.4
		Resilency	0.5
Aquifer control	0.1	Vulnerability	1
		Failure frecuency	0
		Resilency	0
Flood Control	0.05	Vulnerability	0
		Failure frecuency	0
		Resilency	1
Recreation	0.05	Vulnerability	0.5
		Failure frecuency	0
		Resilency	0.5

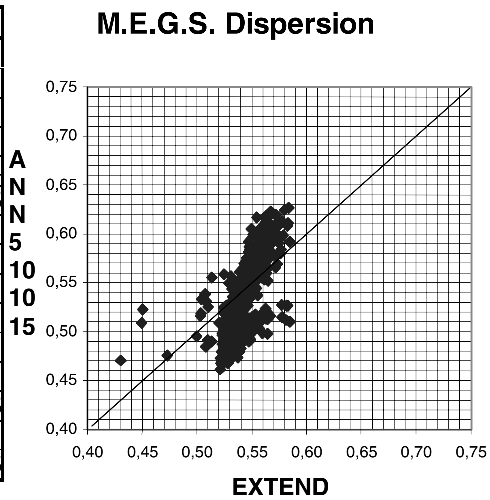


Figure 9 Comparison of MEGS calculated using the ANN model and the simulation model in Extend© (Example 2).

Table 1 Absolute percent errors in scale 0.7 of the ANN model for 500 test examples

Purpose	Index	Maximum	Minimum	Average	Standard deviation
Irrigation	Vulnerability (VR)	15.170	0.001	1.363	1.524
	Probability of failure (OFR)	19.973	0.014	3.339	2.852
	Complement of resilience (RR)	18.159	0.004	3.379	2.675
Energy	Vulnerability (VE)	15.086	0.003	3.613	2.541
	Probability of failure (OFE)	16.167	0.074	3.565	2.804
	Complement of resilience (RE)	22.765	0.006	3.721	3.304
Ponding control	Vulnerability (Van)	6.426	0	1.322	1.295
	Probability of failure (OFAn)	16.661	0	3.076	2.649
	Complement of resilience (RAn)	19.323	0	4.375	3.131
Flood control	Vulnerability (VCre)	38.879	0	6.177	8.117
	Probability of failure (OFCre)	24.729	0	3.232	4.155
	Complement of resilience (Rcre)	31.209	0	4.496	6.265
Recreation	Vulnerability (Vrec)	10.253	0	1.493	1.317
	Probability of failure (OFRec)	10.050	0	2.759	2.024
	Complement of resilience (RRec)	10.272	0	2.979	2.369

Table 2 Errors for Examples 1 and 2

Example	Item	MEGS	Error (%)	Difference	Relative error (% of max.)
1	Maximum	0.73	12.3	0.07	9.8
	Minimum	0.46	−16.5	−0.08	−10.5
	Average	0.61	1.3	0.01	1.01
	Standard deviation	0.04	5.1	0.03	4.22
2	Maximum	0.63	12.8	0.07	11.9
	Minimum	0.43	−15.9	−0.07	−11.44
	Average	0.54	1.13	0.01	0.95
	Standard deviation	0.03	5.63	0.03	4.89

function (replacing variable $I(i, j)$). The resulting equation is shown in Fig. 10.

Next, the search of the best operation alternative was formulated as a nonlinear optimization problem. The best management alternative is that set of operation parameters that minimize the value of MEGS for the planning period. The search is restricted to the range of feasible solutions. SARH-2000 carries out this search in a simple form through interfaces developed in Visual Basic, using the GRG2 algorithm for the Newton conjugate gradient method for an n-dimensional space (Lasdon *et al.*, 1978; Lasdon and Waren, 1979). Figure 11 shows the evolution of MEGS index for a period of 323 months. The legend shows the value of the index at the end of the simulation period. This value gives the user an indication of the overall behavior of the operation policy for the total period of analysis.

The potential of the ANN is evident when comparing the minimum value of MEGS given by the ANN model (MEGS $= 0.13$) and the one given by the Extend© simulation model with the same operation parameters (MEGS $= 0.09$). If a maximization problem with the same objective function and restrictions is processed, the optimization model gives a maximum value of MEGS $= 0.29$ at the end of the period of analysis, similar to the one given by the Extend© model (MEGS $= 0.26$).

These results show that the ANN model has encapsulated correctly the space of operational results simulated with the Extend model and that it is capable of producing good results in situations

$$MEGS = \sum_{i=1}^{5} b_i \sum_{j=1}^{3} p_{i,j} \cdot \left(\frac{\sigma\left(\sum_{m=1}^{10} w_{3,4,m(i.j+(i-1).(j-1))} . \sigma\left(\sum_{n=1}^{10} w_{2,3,n,m} . \sigma\left(\sum_{p=1}^{5} w_{1,2,p,n} . X_p\right)\right)\right)}{I_{\max_{i,j}}} \right)$$

Nomenclature

$\sigma(y) = \frac{1}{1+e^{-y}}$

$\sigma =$ sigmoid function

$y =$ argument of sigmoid function

$p =$ input neuron index [1 : 5]

$n =$ index of neurons of hidden layer 1 [1 : 10]

$m =$ index of neurons of hidden layer 2 [1 : 10]

$X_p =$ input variable of input layer p

$l = i \cdot j + (i-1) \cdot (j-1) =$ index of output neurons [1 : 15]

$i =$ water use [1 : 5]

$j =$ failure index [1 : 3]

$w_{3,4,m,(i.j+(i-1).(j-1))} =$ weights for output of second hidden layer

$w_{2,3,n,m} =$ weights for output of first hidden layer

$w_{1,2,p,n} = \pm weights$ for output of input layer

$b_i =$ relative weight for water use i

$p_{ij} =$ relative weight for index of failure j of water use i

$I_{\max_{i,j}} =$ maximum observed value for 3500 simulations of index of failure j of water use i

Figure 10 MEGS equation using the ANN formulation.

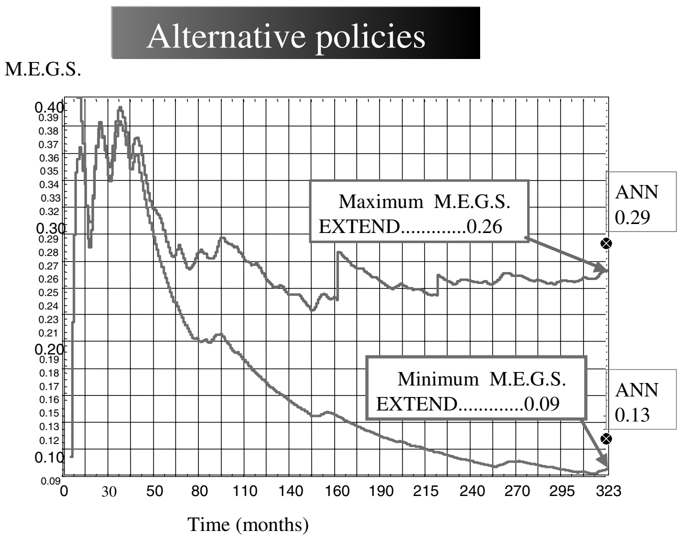


Figure 11 Operation alternatives for 323 months.

not included in the learning duples. The inclusion of the ANN model in the nonlinear optimization scheme produces an optimal operational alternative in a few seconds, result which cannot be obtained using conventional simulation.

5 Conclusions

This model offers a dynamic tool to represent a water resource system and to search for optimal management policies. Key concepts are simulation of continuous processes, ANNs, optimization methods, use of operation rules expressed parametrically, calculation of measures of effectiveness for different uses of water and relative weighting of these measures. Measures of effectiveness can also be related to economic, physical or mixed targets, according to what the user desires. The combined use of simulation and optimization was achieved by the use of ANNs to encapsulate the results of simulation in a simple nonlinear model, which can be incorporated in the structure of the optimization model to search for good administration practices in the space of feasible policies. These policies can easily be constructed when operation rules are expressed in parametric form.

The use of occurrence of failure indicators gives the manager an element to evaluate the risk of an operation rule. The indexes of resilience and the probability of failure incorporate knowledge on the reaction capacity of the system after failure. This information is valuable for deciding which operation policies fulfill management objectives.

ANNs capture the behavior of the system under different operation scenarios and have the capacity to learn several concepts simultaneously, giving the possibility of encapsulating the results of simulation. Since neural networks are continuous and derivable functions they can be used in the objective function of the optimization model. Neural networks trained with a large number of simulation examples, have a good generalization potential and are able to recognize new situations different from the training examples.

Customizing the relative weight of each purpose independently allows the user to include the dynamics of the competition between water uses, without modifying the simulation model and the neural network. Thus, the decision support system can easily incorporate structural modifications, changes in operation rules and failure definitions without modifying methodological aspects.

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