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A Neural Networks Approach for Deriving Irrigation Reservoir Operating Rules

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Abstract. A neural networks approach is applied to the derivation of the operating rules of an irrigation supply reservoir. Operating rules are determined as a two step process: first, a dynamic programming technique, which determines the optimal releases by minimizing the sum of squared deficits, assumed as objective function, subject to various constraints is applied. Then, the resulting releases from the reservoir are expressed as a function of significant variables by neural networks. Neural networks are trained on a long period, including severe drought events, and the operation rules so determined are validated on a different shorter period. The behaviour of different operating rules is assessed by simulating reservoir operation and by computing several performance indices of the reservoir and crop yield through a soil water balance model. Results show that operating rules based on an optimization with constraints resembling real system operation criteria lead to a good performance both in normal and in drought periods, reducing maximum deficits and water spills.

Key words: dynamic programming, irrigation reservoir, neural networks, operating rules

1. Introduction

The occurrence of severe and frequent droughts in the last years has pointed out the need to improve reservoir operation rules, to aid water supply operators to cope with the risk of dramatic water deficiency to users (Cancelliere *et al*., 1998). Traditional approach to reservoir operation studies is based on the use of optimization and simulation models. In particular, definition of operating rules has been generally pursued by making use of optimization techniques, which allow to calculate, on the basis of a given inflow series to the reservoir, the corresponding series of optimal releases, i.e. releases which minimize or maximize a given objective function (Yeh, 1985; Simonovic, 1992; Wurbs, 1993). Then, following an approach proposed by Young (1967), such series of optimal releases have been generally expressed as a function of reservoir state variables and hydrologic input (storage, inflows, etc.), by regression equations which ultimately allow the water managers to determine the water to be released as a function of available information (Bhaskar and Whitlach, 1987; Karamouz and Houck, 1987).

Application of regression techniques however finds a limitation in the necessity to define explicitly the mathematical form of the link between independent and dependent variables. To partly overcome such difficulty, a new interpolation method based on Neural Networks (NN) has been recently applied to the determination of operating rules. NN are able to approximate a wide range of multivariate linear and non-linear functions, while maintaining very good generalization capabilities, and therefore they are ideal candidates when the relationship among the variables is unknown.

Reviews of the state of the art about NN applications in hydrology were recently published in *ASCE* (2000) and Govindaraju and Ramachandra (2000), showing the increasing interest in neural networks during last years in many hydrology related areas, such as rainfall-runoff modeling, streamflow forecasting, ground water, precipitation forecasting, and water quality issues. In water management, NN have been applied for deriving reservoir operating policies with respect to different types of water supply systems (Raman and Chandramouli, 1996; Rossi *et al*., 1999; Jain *et al*., 1999; Cancelliere *et al*., 2000; Chandramouli and Raman, 2001).

In the present article the combined use of a soil water balance model, dynamic programming and neural networks techniques is applied for deriving operating rules of an irrigation supply reservoir. In particular, water demands are computed by averaging monthly irrigation requirements obtained through a soil water balance model, then optimal releases are computed by the application of Dynamic Programming (DP) adopting the sum of squared deficits objective function. Operating rules are derived by expressing the results of DP optimization on a long training period containing a severe drought period using NN techniques; then the obtained operating rules are validated by simulating the behaviour of the reservoir on a different short period. The behaviour of the different trained networks (operating rules) is assessed by simulation in terms of squared deficits with respect to water demands, of reservoir performance indices (including reliability and vulnerability) and of a crop yield index.

2. Theory

2.1. DYNAMIC PROGRAMMING MODELS

Determination of optimal releases from an irrigation reservoir must take into account, either implicitly or explicitly, how such releases will affect agricultural yield losses. Although exact agricultural yield losses consequent to deficits are difficult to be estimated, due to their dependence on several factors such as the type and timing of the crop being irrigated, its stage of growth, etc., in general terms, they can be approximated by a function of the ratio between actual and maximum evapotranspiration (Doorenbos and Kassam, 1979).

Direct determination of optimal releases that minimize yield losses however can be cumbersome, due to the dependence of actual evapotranspiration ETa on present and past releases through the soil water balance. In this work, following a consolidated approach, optimal releases have been computed using as objective function the sum of the squared deficits with respect to fixed mean monthly crop requirements as demand levels. Adopting such demand levels D_t, the optimization problem can be stated as follows:

$$\text{Minimise:} \qquad s = \sum_{t=1}^{N} (D_t - U_t)^2 \ , \tag{1}$$

subject to the reservoir hydrological balance constraints:

$$S_t = S_{t-1} - U_t + I_t - E_t \qquad t = 1, \ldots, N \tag{2}$$

$$0 \leq S_t \leq K$$

$$0 \leq U_t$$

where

t	=	current time interval (month);
D_t	=	irrigation demand in stage t;
U_t	=	release from reservoir in stage t;
S_t	=	volume stored in the reservoir at the end of stage t;
K	=	storage capacity of the reservoir;
I_t	=	reservoir inflow during stage t;
E_t	=	evaporation losses from reservoir during stage t;
N	=	total number of optimisation stages.

Note that in the above formulation, other losses besides evaporation have been neglected, although they could be easily included, if significant. Implementation of the above optimization problem within a DP framework can be pursued by considering the following recursive equation for any stage t:

$$f_t^n(S_t) = \min\left[Z_t + f_{t+1}^{n-1}(S_{t+1})\right] \ , \tag{3}$$

where $Z_t = (D_t - U_t)^2$ when $U_t \leq D_t$
and $Z_t = (U_t - D_t)$ when $U_t > D_t$

subject to the state Equation (2) and to the constraints on stored volume and releases. Note that the two conditions on Z_t in Equation (3) allow to take into account the presence of spills, which otherwise would have the same weight of deficits thus leading to unrealistic solutions. More specifically, if a quadratic objective function would be considered also for spills, the algorithm would tend to distribute spills over several stages, by reducing the stored volume, which is in contrast with a reservoir management mainly devoted to water conservation.

Straight application of the above algorithm however can lead to unrealistic sequences of releases, since a perfect knowledge of future inflows and evaporation rates is assumed, and thus apparently unnecessary deficits might be imposed on demands because of the presence of drought periods possibly far ahead in the future. Therefore, the above algorithm has been slightly modified by introducing a penalty term enforcing more realistic solutions. In particular, reservoir releases equal to irrigation demands were imposed when reservoir storage exceeds a fixed percentage of maximum storage. In the following, this DP approach is called CDP (Constrained DP).

2.2. SOIL WATER BALANCE MODEL

Evaluation of crop water requirements and of agricultural yield losses requires the computation of total actual evapotranspiration in a given month. In general terms, the actual evapotranspiration rate will depend on the maximum evapotranspiration rate for that month and for the particular crop under investigation, as well as on the soil water content. The latter must be assumed variable during a given month and therefore in general the evapotranspiration rate will vary along the month. Computation of total evapotranspiration in a given month must therefore be preceded by the determination of the soil water content as a function of time, which can be pursued by means of a simplified soil water balance model.

Assume that the soil water balance in a given month can be represented by the continuity equation for the top soil layer of capacity $C_{\max}$, where all inputs and outputs besides vertical infiltration and evapotranspiration are neglected, expressed by a differential equation of the type:

$$R(\tau) - ETa(\tau) = \frac{dC(\tau)}{d\tau}\ , \tag{4}$$

where

$R(\tau)$	=	infiltration rate (net irrigation and/or net precipitation) assumed constant (e.g. mm day^{-1});
$ETa(\tau)$	=	rate of actual evapotranspiration (e.g. mm day^{-1});
$C(\tau)$	=	soil water content (e.g. mm), $C_t(\tau) \le C_{\max}$;
τ	=	is the current time within the month t, varying from the beginning ($\tau = 0$) to the end of the month ($\tau = T$) ($0 \le \tau \le T$).

Further, assume that the rate of actual evapotranspiration is a function of the soil water content $C(\tau)$ like the one depicted in Figure 1.

In Figure 1 *ETm* is the maximum evapotranspiration for the given month and *OYT* (Optimum Yield Threshold) is a threshold level for C below which the plant is assumed under stress and consequently the actual evapotranspiration is less than the maximum one, leading to some crop yield reduction.

The aim here is to determine the soil water content at the end of the month $C(\tau = T)$, given initial condition Co and precipitation plus irrigation rates R

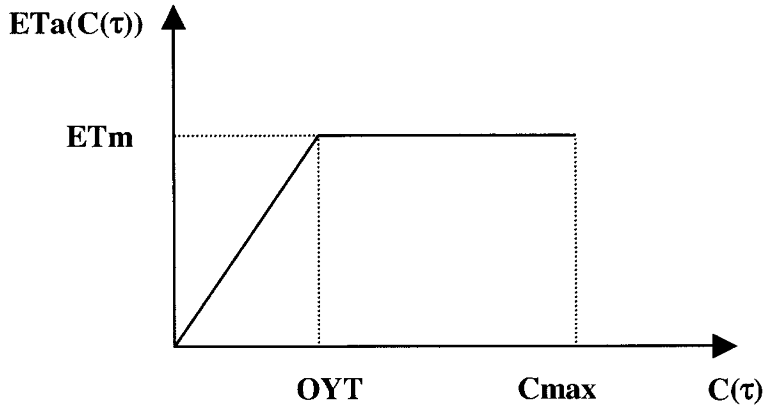

Figure 1. Actual evapotranspiration $ETa(\tau)$ as a function of the soil water content $C(tau)$.

constant. Further, knowledge of $C(T)$ will provide directly the total actual evapotranspiration in the month by means of a water balance. Note that the assumption of infiltration rate R constant throughout the time interval is not limiting since one can always split the integration of Equation (4) into sub-periods where R can be assumed constant.

Integration of Equation (4) is not straightforward due to the particular form of *ETa(C)*. However it can be integrated by considering two separated regions namely $C \leq OYT$ (region 1) and $C > OYT$ (region 2). As long as $C(\tau)$ remains within each of these two regions, Equation (4) can be integrated directly.

In particular, when $C(\tau) \leq OYT$ the following differential equation will hold:

$$R(\tau) - kC(\tau) = \frac{dC(\tau)}{d\tau} , \tag{5}$$

with $k = ETm/OYT$, and the constraint $C(\tau) \geq 0$.

When $C(\tau) > OYT$, the following differential equation will be valid:

$$R(\tau) - ETm(\tau) = \frac{dC(\tau)}{d\tau} \tag{6}$$

with the constraint $C(\tau) \leq C_{\max}$.

Therefore it is necessary to distinguish between the two regions. Furthermore, it is evident that the behaviour will change according to whether $R > ETm$ or $R \leq ETm$. Thus, integration of Equation (4) can be carried out considering four distinct cases, as shown in Table I.

Once the soil water content at the end of the month $\tau - T$ is known, it is also possible to compute the total evapotranspiration during the interval $(0, T)$ ETa_T. This can be computed simply by considering the overall water balance during the interval $(0, T)$:

$$R \cdot T - ETa_T = C(T) - Co \Rightarrow ETa_t = Co - C(T) + R \cdot T \ . \tag{7}$$

Table I. Soil water content *C(T)* obtained by integrating the soil water balance equation

	Co>OYT	***Co≤OYT***
R>ETm	$C(T) = \min\left[Co + (R\text{-}ETm)T, Cmax\right]$	$C(T) = \begin{cases} \dfrac{kCo + Re^{kT} - R}{ke^{kT}} \Leftrightarrow T \le Tc \\ \min\left[OYT + (R\text{-}ETm)(T\text{-}Tc), Cmax\right] \Leftrightarrow T > Tc \end{cases}$ where: $Tc = \dfrac{1}{k}\ln\dfrac{R - kCo}{R - kOYT}$
R≤ETm	$C(T) = \begin{cases} Co + (R\text{-}ETm)T \Leftrightarrow T \le Tc \\ \dfrac{kOYT + Re^{k(T-Tc)} - R}{ke^{k(T-Tc)}} \Leftrightarrow T > Tc \end{cases}$ where: $Tc = \dfrac{Co - OYT}{ETm - R}$	$C(T) = \dfrac{kCo + Re^{kT} - R}{ke^{kT}}$

The above relationship, along with the integration of Equation (4) allows to determine the total evapotranspiration in a given interval, given irrigation release, precipitation depth, maximum evapotranspiration and initial soil water content Co.

2.3. MULTILAYER FEED-FORWARD NEURAL NETWORKS

A neural network can be defined as ‘a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use’. This technique finds inspiration from biological neural systems, so that the processing units are called neurons; they can be variously connected, composing different structures of neural networks. It resembles the brain in two respects:

(1.) Knowledge is acquired by the network through a learning process;
(2.) Interneuron connection strengths known as synaptic weights are used to store the knowledge’ (Govindaraju and Ramachandra, 2000).

Some of the reasons why NN should be preferred to other techniques are the following:

a) In opposition to Artificial Intelligence approach, NN require no programming: they can be trained directly from the data;
b) NN are massively parallel: this allow them to gain high speed performance in decision making;
c) NN have, under some hypotheses, the ability to generalize, i.e. to extend their decision making to novel data not seen by the network during the training;
d) NN can be successfully applied when a complex decision region is required: for example in classification or pattern recognition.

The most commonly used architecture of NN is the multilayer feedforward neural network, characterized by the presence of one or more hidden layers, whose computation nodes are called hidden neurons or hidden units. The nodes in the input layer simply apply the input signals to neurons (computation nodes) in the first hidden layer. The output signals of the second layer are used as inputs to the third layer, and so on until the last layer. The neurons in each layer receive as their inputs only the outputs of all the neurons in the preceding layer, i.e. the input signal propagates through the network in a forward direction, on a layer-by-layer basis. These neural networks are commonly called multilayer perceptrons (MLPs).

The input signal to the generic neuron is constituted by a linear combination of the outputs of neurons belonging to the preceding layer; such input signal is then processed by a so called activation function, which is non decreasing and ranged between 0 and 1. The logistic function is usually used:

$$\varphi(\xi) = \frac{1}{1 + e^{-\xi}} \ , \tag{8}$$

where ξ is the input signal to the neuron and φ (ξ) the output (Hassoun, 1995). This function is largely used because of the convenient mathematical expression of its derivate, which allows simplification in deriving training algorithms.

If the function to be mapped is linear, the following activation function can be used:

$$\varphi(\xi) = \xi \ , \tag{9}$$

with no hidden layer. In this case the network is equivalent to a linear regression equation.

The link between neurons belonging to different layers is made by linear relationship whose coefficients, called weights, constitute the set of parameters, to be estimated by appropriate algorithms. The search of optimal weights vector, i.e. the training algorithm, is performed on the basis of a comparison between targets and NN output values, choosing the set of parameters that generate the minimum error. Although it is possible to utilize traditional numeric optimization procedures, such as conjugate gradient descent, generally the training is done by the so called *back-propagation method*. Back-propagation is essentially a gradient descent method that minimizes the network error function:

$$E = \sum_{P} \sum_{p} (d_i - y_i)^2 \ , \tag{10}$$

where d_i and y_i are the estimated and the target value, respectively, p is the number of output nodes and P the number of training patterns.

This error is propagated backward through the network to each node, and the weights are adjusted based on equation:

$$\Delta w_{ij}(n) = \alpha \frac{\partial E}{\partial w_{ij}} + \eta \Delta w_{ij}(n-1) \ , \tag{11}$$

where Δw_{ij} (n) and Δw_{ij} $(n-1)$ are the weights increment between node i and j during the nth and *(n – 1)*th iteration. In Equation (11) α and η are called learning rate and momentum. Learning rate influence the speed of convergence, but can lead to oscillation in the weights, so the momentum factor is used to stabilize the solution.

Back-propagation is an iterative algorithm, thus it needs some index to decide when it must be stopped. Usually a quadratic form index is adopted, which gives the root mean squared errors (*RMSE*) between targets and network outputs:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(d_i - y_1)^2}{N}}\,. \tag{12}$$

3. Application

3.1. SYSTEM UNDER INVESTIGATION: IRRIGATION REQUIREMENTS

Pozzillo reservoir on Salso river (tributary of Simeto river, the main Sicilian water course) was selected as a case-study. Net storage is equal to 123 $\times$ 10^6m^3 while the basin area is equal to 577 km^2. The reservoir is part of a multipurpose system (hydroelectric, irrigation, and municipal) which includes another reservoir, three diversions, and five hydroelectric plants.

The system supplies the Catania Plain irrigation district whose water conveyance and distribution network is operated by the Land Reclamation Consortium. The irrigated area of the district is about 18.000 ha, and citrus is the prominent crop (more than 90%). Irrigation volumes are delivered by the Land Reclamation Consortium at fixed intervals, and microirrigation is the most widespread irrigation technique.

Operation of Pozzillo reservoir started on 1964. Recent drought events have pointed out the need of revised operating rules, able to cope effectively with water deficiency and to mitigate the worst irrigation deficits. For example, during 1990, at the end of a three year drought period, the annual release was only 7% of the average, due to the depletion of the stored water in previous years.

Available data for the observation period 1962–1998 include:

– monthly streamflow series of Salso river at Pozzillo reservoir during the years 1962–1998, estimated by means of a hydrologic balance of the reservoir;
– monthly evaporation rates calculated as a function of the mean monthly temperature;
– monthly areal precipitations over the irrigation district;
– monthly reference and maximum evapotranspiration for the irrigation district.

Annual streamflow series (hydrologic year October–September), shown in Figure 2, presents a high variability between the maximum value equal to 373.6 $\times$ 10^6m^3 (647.5 mm) which occurred on 1972 and the minimum value 3.3 $\times$ 10^6m^3 (5.7 mm), which occurred on 1989. The mean value is 94.0 $\times$ 10^6m^3 (162.9 mm). The most severe drought period was experienced during the three years 1988–1990, during which, total streamflow volume was below, 58.0 $\times$ 10^6m^3 and crop yield decreased significantly.

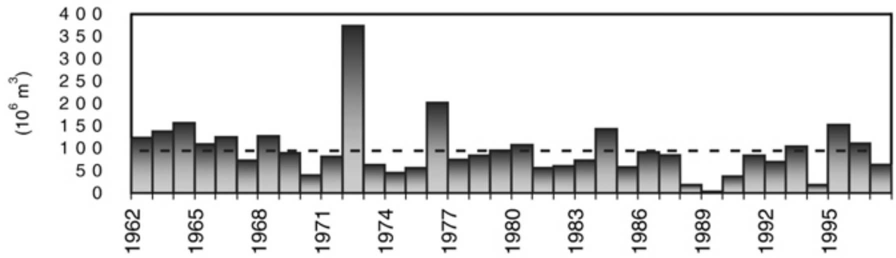

Figure 2. Annual streamflow series (hydrologic year) of Salso river at Pozzillo dam during the period 1962/1963–1997/1998 and mean annual streamflow.

Table II. Averaged monthly irrigation demands

	May	June	July	August	September	October	Total
Demand (10^6 m^3)	3.5	11.6	24.6	25.5	17.3	5.5	88.0

Since citrus is the prominent crop in the irrigation district, irrigation demands have been computed by averaging the irrigation requirements obtained by the soil water balance model described before, by considering losses in conveyance and distribution of about 25%. Applying the model with relevant pedological features of irrigated soil and with monthly values of precipitations and temperatures related to period 1962–1991, the following values were obtained:

– mean yearly demand 357.5 mm;
– minimum yearly demand 181.0 mm in 1972;
– maximum yearly demand 600.0 mm in 1981.

Mean monthly demands during the irrigation season are reported in Table II.

3.2. NEURAL NETWORKS TRAINING

Dynamic Programming and Constrained Dynamic Programming were applied using historical inflow series during 1962–1991 period, thus obtaining the optimal reservoir releases series Er_t during the irrigation season, which in absence of spills, are equal to U_t. Both dynamic programming models were implemented through the generalized DP package CSUDP (Labadie, 1999). A neural network approach was then applied to determine optimal releases as a function of available information at the beginning of month. Since no inflows forecast was assumed, the selection of input variables was limited to storage volume and release at previous month. The results of the optimization models DP and CDP were used as training patterns. The CDP model was run using a stored volume of 100×10^6 m^3 as a threshold above which satisfy fully the monthly demand.

Determination of the operating rules was carried out by training six different networks (one for each irrigation month). The optimal number of neurons in the hidden layer was determined by an heuristic procedure, following the experience of a previous study (Cancelliere *et al.*, 2000). A preliminary analysis of both DP and CDP results showed an almost perfect linear relationship between optimal releases in a given month and the releases in the previous month for July–October and June–October, respectively, as a consequence of the adopted quadratic objective function and of the limited inflows in these months. Then, networks with three neurons in the hidden layer and logistic activation function were adopted for the months exhibiting a non linear relationship between input and output variables (i.e. May-June and May for DP and CDP, respectively). In the remaining months, one neuron networks with linear activation functions were adopted. Training was carried out by backpropagation procedure with momentum term and considering a stopping criterion based on an RMSE threshold.

After training of the networks, a simulation model that determines monthly net releases Er_t according to the NN operating rules was applied and the following reservoir performance indices were computed:

– sum of squared deficits $\Sigma(D_t - Er_t)^2$;
– volumetric reliability $\Sigma Er_t / \Sigma D_t$;
– deficit frequency;
– minimum of the ratios between monthly actual and maximum evapotranspiration, min (ETa_t/ETm_t), which was assumed as a proxy of agricultural yield.

Actual evapotranspiration in each month consequent to irrigation releases has been computed by means of the integration of the soil water balance.

In Table III are reported, for each set of NN considered, the input variables, the sum of squared deficits, the volumetric reliability, the deficit frequency and the minimum of the ratios between monthly *ETa* and *ETm* in 1962–1991 period. The results of DP and CDP optimization runs are also reported for comparison.

It can be inferred from the table that NN(DP), trained using as data pattern DP results, are more conservative than NN(CDP), thus leading to a lower sum of squared deficits. However, NN(DP) never satisfy fully the monthly demand (deficit frequency 100%), regardless of the storage levels, which is obviously unacceptable from a practical standpoint. NN(CDP) on the other hand release the demand D_t when storage is bigger than threshold fixed in CDP optimization, thus leading to a lower deficit frequency (69%) and a slightly higher volumetric reliability. The difference of behaviour of the two rules can be inferred from Figure 3 where the releases in the month of May are plotted vs. initial storage in the same month for the two optimization runs and for the two NN rules. The plot shows that DP releases present a fairly large spread even for full reservoir levels (from no release to full demand), and consequently the trained NN(DP) never release fully the demand since it is not able to capture such variability. CDP releases on the other hand are

Table III. Input variables, sum of squared deficits, volumetric reliability, deficit frequency and minimum monthly ratio between actual and maximum evapotranspiration during 1962–1991 period for analyzed neural networks and optimization models DP and CDP

	Months			$\Sigma(D_t - Er_t)^2$ $(10^6\ \mathrm{m}^3)^2$	$\Sigma Er_t / \Sigma D_t$ (%)	Deficit frequency (% months)	min(ETa_t/ ETm_t) (%)
	May	June	July–October				
NN(DP)	S_{t-1}	S_{t-1}; Er_{t-1}	Er_{t-1}	3925	81	100	27
NN(CDP)	S_{t-1}	Er_{t-1}	Er_{t-1}	4057	83	69	27
DP	–	–	–	2497	82	76	36
CDP	–	–	–	3987	83	49	27

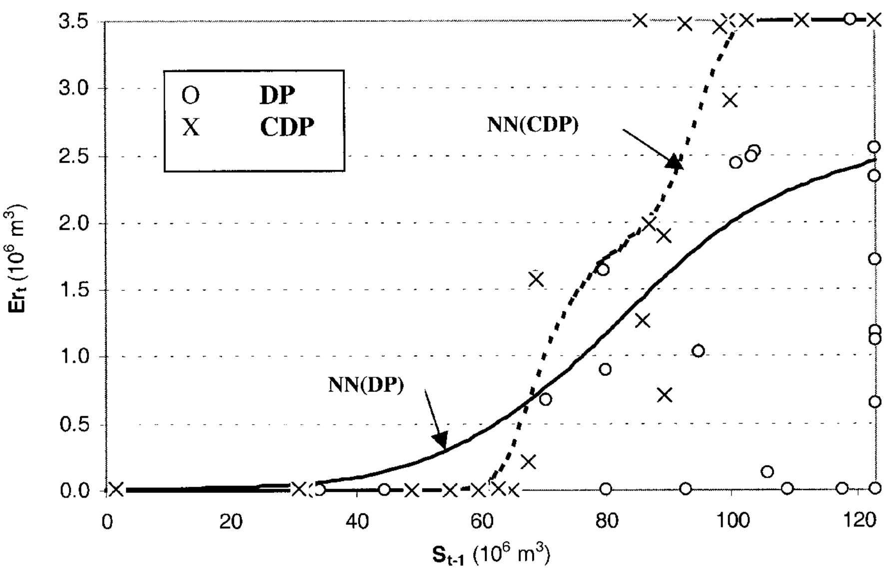

Figure 3. DP and CDP optimal releases for May and NN releases as functions of storage volume.

always equal to the demand for storage levels above 100×10^6 m^3 and NN(CDP) reflects such behaviour, thus leading to more realistic operating rules.

3.3. VALIDATION OF OPERATING RULES

The validation of the selected operating rules was performed by simulating reservoir operation during 1992–1998 period, not included in the training period. A simulation applying the so called SOP (Standard Operating Policy) rule, i.e. a policy that releases the demand in each month if there is available water stored, was also carried out for comparison purposes. Such policy can be considered close to the management practices currently in use for Pozzillo reservoir. Further, optimization of releases during the same period using DP and CDP was also carried out. Such optimization runs represent a theoretical optimal management, under the perfect knowledge of the future and as such, they are useful only for comparison purposes.

Results of simulation and optimization runs were compared on the basis of the following reservoir performance and crop yield indices:

– volumetric reliability $\Sigma Er_t / \Sigma D_t$;
– sum of squared deficits $\Sigma(D_t - Er_t)^2$;
– deficit frequency;
– deficit mean length;
– maximum seasonal deficit;
– total spills;
– minimum (ETa_t/ETm_t).

The above indices are reported in Table IV, from which it can be inferred that both NN(DP) and NN(CDP) outperform the SOP rule in terms of smaller sum of squared deficits, smaller maximum seasonal deficit and greater minimum ratio between actual and maximum evapotranspiration. On the other hand, SOP leads to greater volumetric reliability, less average length of deficit periods and smaller spills. The above findings are consistent with the fact that NN rules are conservative while the SOP does not impose deficits unless it is necessary to do so.

Table IV shows also that unconstrained DP leads to overall best results in terms of sum of squared deficits, as expected, and crop yield index. However, CDP approach performs better in terms of volumetric reliability and deficit frequency, and almost as well in terms of spills and crop yield index, although the sum of squared deficits and the maximum seasonal deficit range are slightly worse. This is consistent with the less conservative nature of CDP.

The results of the application of the two dynamic programming approaches is fully reflected by the corresponding results obtained by applying the corresponding neural network based operating rules. Indeed, NN(DP) lead to more conservative rules while NN(CDP) ensure higher volumetric reliability, reduced water spills and similar performance in terms of other indices.

In Figure 4, time series of sum of squared deficits, seasonal deficit and the min*(ETa/ETm)* are shown. The presence in the validation period of a particularly severe drought year (1995), emphasizes the opportunity to use networks in place of SOP rule, whose simulation run leads to maximum seasonal deficit and generally reduced annual crop yield.

Table IV. Performance indices of the reservoir operation and crop yield index during 1992–1998 period by using optimization models DP and CDP, the neural networks NN(DP) and NN(CDP) and SOP rule

	$\Sigma Er_t/\Sigma D_t$ (%)	$\Sigma(D_t - Er_t)^2$ $(10^6\ m^3)^2$	Deficit frequency (% months)	Deficit mean length (months)	Maximum seasonal deficit $(10^6\ m^3)$ *(% demand)*	Total spills $(10^6\ m^3)$	Minimum ETa_t/ETm_t (%)
NN(DP)	81	765	100	6	57–65%	40	42
NN(CDP)	83	869	71	6	62–70%	37	39
SOP	85	1600	21	3	65–74%	35	36
DP	83	465	57	6	30–34%	35	50
CDP	84	712	55	6	52–60%	35	42

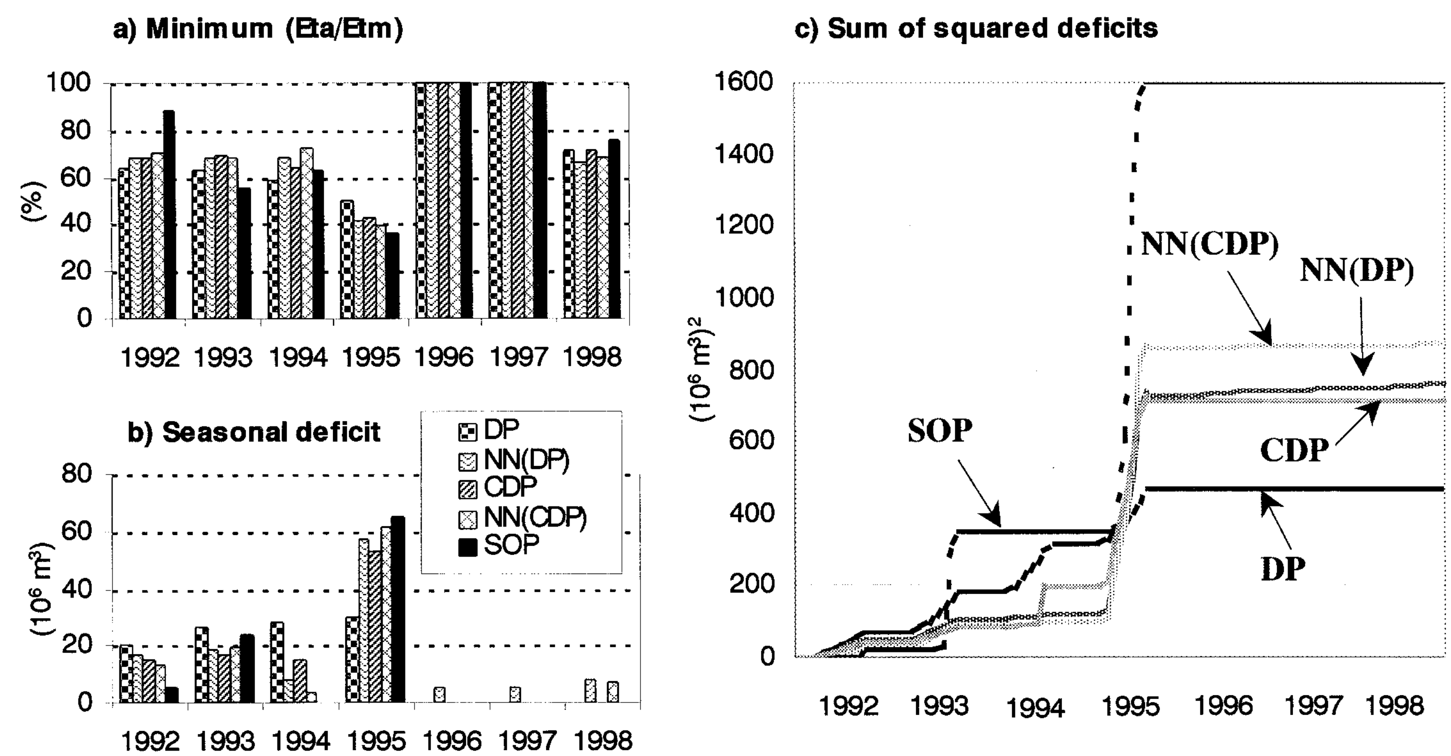

Figure 4. Comparison between operating rules given by neural networks NN(DP) and NN(CDP), SOP, DP and CDP optmization during 1992–1998 period: (a) min (Eta/Etm), (b) Seasonal deficit, (c) Sum of squared deficits.

4. Conclusions

Monthly operating rules for an irrigation reservoir have been derived by interpolating the results of the application of two Dynamic Programming models (DP and CDP), based on sum of squared deficits objective function, by using neural networks techniques. The two models differ by the presence in CDP of a penalty term enforcing optimal releases series to follow the real system managing criteria, taking explicitly into account the social and management constraints to release water demand when reservoir storage volume exceeds a fixed threshold. The obtained operating rules have been validated by simulating the behaviour of the reservoir over a shorter period, not included in the period used for training the networks, and through simulation of the soil water balance for evaluating a crop yield index.

Validation of selected neural networks over a seven years period showed the superiority of networks trained on CDP pattern. In fact, networks trained on DP pattern resulted more conservative than others, and never met the total demand, independently from reservoir storage conditions. On the contrary, networks trained on CDP pattern show to learn CDP operation criteria, thus obtaining best results in terms of reservoir operation indices, and performing only slightly worse in terms of sum of squared deficits.

Results show that the use of neural networks should improve the reservoir performances during drought conditions, thus confirming the general enhancement achieved by using neural networks in many other hydrological fields.

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Appendix

The following symbols are used in this article:

$C(\tau)$	Soil water content (mm);
$C_{\max}$	Capacity of the soil (mm);
Co	Initial soil water content (mm);
d_i	Estimated values of target values (10^6 m^3);
D_t	Irrigation demand at month t (10^6 m^3);
E	Network error function (for the entire training set) (10^6 m^3)^2;
E_t	Evaporation losses from reservoir during month t (10^6 m^3);
Er_t	Net reservoir release during month t (10^6 m^3);

ETa, ETa(τ)	Total actual evapotranspiration (mm) and evapotranspiration rate (mm day^{-1}) for a given month;
ETa$(C(\tau))$	Rate of actual evapotranspiration as a function of soil water content (mm day^{-1});
ETm, ETm(τ)	Maximum total evapotranspiration (mm) and evapotranspiration rate (mm day^{-1}) for a given month;
I_t	Reservoir inflow during month t (10^6 m^3);
K	Storage capacity of the reservoir (10^6 m^3);
k	Slope of the function *ETa*$(C(\tau))$ (for $C(\tau) \leq C_{\max}$);
n	Number of iterations sequentially performed in back-propagation algorithm for neural network's training;
N	Total number of optimisation stages;
OYT	Optimum Yield Threshold (mm);
p	Number of output nodes of the neural network;
P	Number of training patterns;
R, $R(\tau)$	Total infiltration (mm) and infiltration rate (mm day^{-1}) for a given month;
RMSE	Root mean square error between the target and the estimated values (10^6 m^3);
s	Objective function of the optimization algorithm;
S_t	Volume stored in the reservoir at the end of stage t (10^6 m^3);
t	Current month;
T	Time upper bound (days) of the month;
U_t	Release from reservoir during month t (including spills) (10^6 m^3);
y_i	Target values (10^6 m^3);
Z_t	Return function of the dynamic programming algorithm;
α	Learning rate of the back-propagation algorithm;
$\Delta w_{ij}(n)$	Weights increment between node i and j during the nth iteration;
η	Momentum of the back-propagation algorithm;
ξ	Input signal to the neuron;
τ	Current time (days) of the month t varying from the beginning ($\tau = 0$) to the end of the month ($\tau = T$);
φ, $\varphi(\xi)$	Neurons' activation function and output of the neurons.

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