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Optimization of Agricultural Water Demand Using a Hybrid Model of Dynamic Programming and Neural Networks: A Case Study of Algeria

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***Abstract*—**In Algeria agricultural irrigation is the primary water consuming sector followed by the domestic and industrial sectors. Economic development in the last decade has weighed heavily on water resources which are relatively limited and gradually decreasing to the detriment of agriculture. The research presented in this paper focuses on the optimization of irrigation water demand. Dynamic Programming-Neural Network (DPNN) method is applied to investigate reservoir optimization. The optimal operation rule is formulated to minimize the gap between water release and water irrigation demand. As a case study, Foum El-Gherza dam's reservoir system in south of Algeria has been selected to examine our proposed optimization model. The application of DPNN method allowed increasing the satisfaction rate (SR) from 12.32% to 55%. In addition, the operation rule generated showed more reliable and resilience operation for the examined case study.

***Keywords*—**Water management, agricultural demand, dam and reservoir operation, Foum el-Gherza dam, dynamic programming, artificial neural network.

I. Introduction

NATURAL water resources in Algeria often depend on rainfall which is very unevenly distributed over the territory and characterized by strong intra-annual irregularities. The increase in the demand for water, which preoccupies the development of the country especially the field of agriculture, has become a major problem for those responsible to meeting irrigation demands. To ensure the country's food security, irrigation services planned a strategy to increase irrigation potential to secure agricultural production, aiming at expanding irrigated areas and improving water supply for agriculture. Usually, reservoirs are built to supplying water for domestic demands, agriculture, industrial and generating hydroelectric power. They are intended to balance the supply and demand of water.

Real-time reservoir operation model for irrigation of multiple crops is proposed by [1]. Two models were developed, an operating policy model, which optimizes reservoir releases across time periods in a year, and an allocation model, which optimizes irrigation allocations across crops within a time period. An empirical interannuel management rule is defined to operate Ghezala reservoir (Tunisia) which destined for irrigation use [2]. Their objective consists of establishing a trade-off between the total quantity of water to be distributed for summer irrigation and the indispensable volumes to be held in store for the raising of future seedlings during the following autumn. They mentioned that the method developed allows to balance the risk of failure all over the year and to adapt the strategy of irrigation according vegetative critical phases of crops. Stochastic dynamic programming technique is applied by [3] for identification of an optimal rule which is based on two opposite objectives, the satisfaction of the irrigation water demand and the safeguard of minimal water storage in the Nebhana dam (Tunisia). They reported that optimal rule permits to estimate the necessary water release volume for irrigation by considering the water storage and the decision period. A fuzzy risk approach is developed for performance evaluation of an irrigation reservoir system [4]. They mentioned that the irrigation decision maker would look for the implications of using the operating policy through answers to the questions such as, how often the system will fail and how quickly it will recover from a failure. Their study is based on concepts that consider the low yield of a culture as a fuzzy event and links it to the definition of risk. Genetic algorithm (GA) is applied by [5] in order to compute the quantity of water that should be released from Upper Wardha reservoir to meet the monthly irrigation demand. A real-coded GA is developed by for optimizing the operation of reservoirs in an on-demand irrigation system. Taking into account the variability of farmers' requirements, demand hydrographs were randomly generated within a pre-determined confidence interval. Reference [6] applied a multi-objective reservoir optimization model using the SCE algorithm to derive reservoir operating rules for the Xinfengjiang (XFJ) reservoir in the East River Basin in southern China. Their objectives are to estimate a variety of irrigation water demands in the downstream of the East River Basin, and to derive a number of optimal strategies for the XFJ reservoir under different priorities to ensure the river's environmental health when minimizing the water supply deficit and maximizing the hydropower generation as well. Reference [7] developed a model using Fuzzy Interference system (FIS) to maximize the benefits of water use for irrigation purpose through Jayakwadi Dam.

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II. Case Study

Foum el-Gherza arch dam is located at 20 km in the East of Biskra over Abiod River (shown in Fig. 1). It was constructed in 1950; the dam height is 73 m with capacity of 36 million m^3

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and watershed area1300 km².

Relation between storage, surface area and elevation of the reservoir are given by:

$$H = 183 + 0.76 * V - 0.01 * V^2 + 8 * 10^{-6} * V^3 \quad (1)$$

$$A = 1.26 + 0.04 * V + 0.001 * V^2 - 10^{-6} V^3 \quad (2)$$

where H: Indicates the reservoir elevation in meters; A: The surface area in Km² and V: The reservoir storage in MCM.

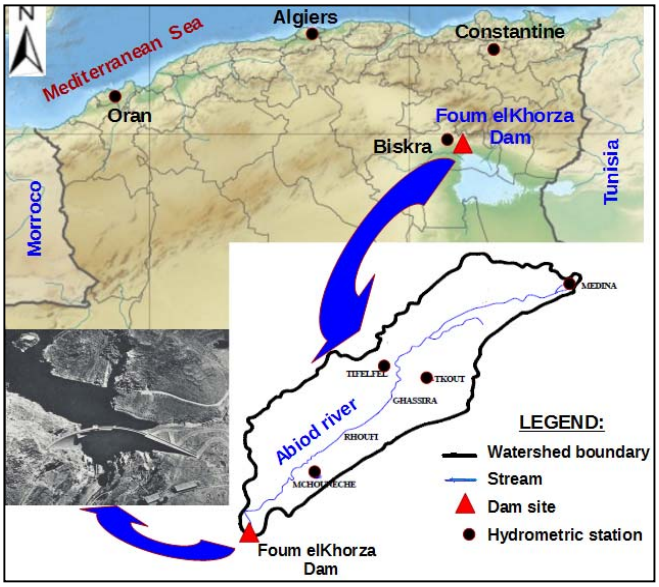


Fig. 1 Foum el-Gherza dam location and watershed delimitation

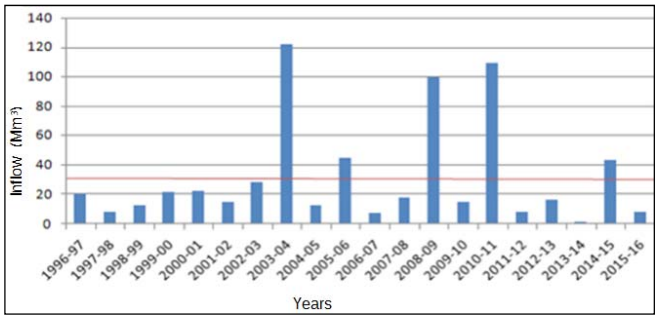


Fig. 2 Mean annual inflow

The mean annual inflows are shown in Fig. 2. The analysis of the mean annual inflow has shown that inflows are often below the annual average which is 32 mm³. Also, we note that the number of dry years increases to 15, while the number of wet years is 5.

Under arid climate, Foum El-Gherza dam is intended to irrigate the palm groves with total area of 850 Ha. The annual irrigation demand is 48MCM just 12.32% is satisfied.

For data period from January 2007 to December 2016, target storage and target releases for each month are derived according to monthly demands (Table II).

III. Reservoir Model Optimization

The objective function is defined as follow.

$$\boldsymbol{OF} = \text{Minimize} \sum_{t=1}^{12} [R(t) - D(t)]^2 \quad (3)$$

where: R(t) and D(t) are agricultural water release and demand in month (t) respectively.

TABLE I
Monthly Mean Inflow and Irrigation Demands in MCM

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean inflow	2,72	6,68	1,37	1,32	1,69	1,04	3,37	5,02	5,85	1,27	0,61	1,13
Irrigation demands	1,86	2,46	3,6	4,77	6,51	8,19	9,3	8,9	6,12	4,28	2,52	1,77

TABLE II
Monthly Target Storage and Releases in MCM

Month	Target storage	Target releases	Minimum eventual release	Maximum eventual release
January	7	0,5	0	1
February	8	1	0	2
March	9	1,5	1	3
April	10	2	1	3
May	10	4	2	5
June	9	4,5	3	5
July	7	5	3	6
August	6	5	3	6
September	7	3	1,5	4
October	9	2	1	3
November	8	1	0	2
December	8	0,5	0	1

The problem is subjected to the following constrains:

$$S(t_{+1}) = S(t) + I(t) - R(t) - L_{os}(t) \quad (4)$$

$$S_{min} < S(t_{+1}) < S_{max} \quad (5)$$

$$R_{min} < R(t) < R_{max} \quad (6)$$

where: $S(t_{+1})$ is the storage volume at period t_{+1}, S(t) is the storage volume at period t. I(t) is the monthly inflow in the reservoir at the month t, L_{es} (t): is the monthly losses from the reservoir at the month t. Smin and Smax are the minimum and the maximum storage of the reservoir. Rmin and Rmax are the minimum and the maximum agricultural water release.

IV. Methods

A. Combining Dynamic Programming and Artificial Neural Network PDNN

The model was solved by dynamic programming, and the optimal policies were derived by backward recursive.

$$F^n(S_t) = \min_{Rt} \{C_t(S_t, R_t) + F^{n-1}(S_{t+1})\} \quad (7)$$

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where: $F^n(S_t)$: Optimal cost in period t for storage S_t; C_t (S_t, R_t): Immediate cost obtained from making decision R_t at stage t; F^{n-1} (S_{t+1}): Cumulative Optimal cost, from period t+1 to final period N.

According to [8], the active storage of the reservoir is discretized into classes and the eventual releases for each month are discretized between minimum and maximum eventual release, the optimum releases for each month is derived.

In order to simulate the reservoir relationship, we used Artificial Neural Network, which has the advantage of identifying non-linear relations between input and output data.

ANN is a neural network consists of a number of neurons that are arranged in an input layer, an output layer and one or more hidden layers.

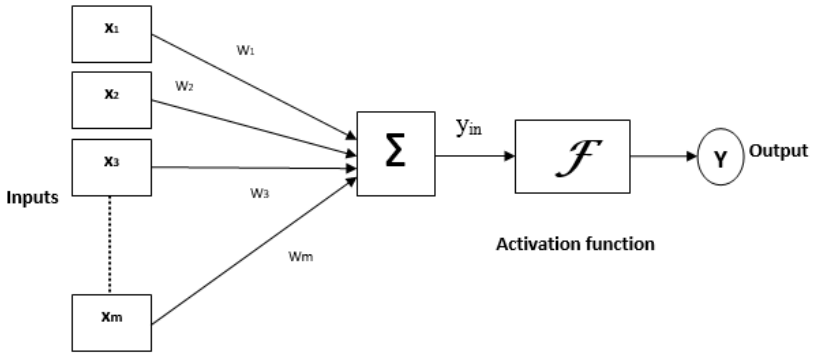


Fig. 3 Typical multi-layer neural network architecture

Information where transformed by a transfer function F is given by:

$$y(k) = F(\sum_{i=0}^{m} w(k) * xi(k) + b) \quad (8)$$

where: x(k): Input value in discrete time k; w(k):Weight value in discrete time k; b: The bias; y(k): Output in discrete time k.

Determining the best values of all the weights is called training the ANN, where the error (difference between desired output and network output) must be minimizing. Back-propagation is the most common algorithm used in the training phase, and the modern second-order back-propagation algorithm, such as Levenberg-Marquardt, is substantially faster. After training, the network was tested by other inputs data set in order to estimate the output. DPNN was applied by [9]-[12].

B. Indices Performance

In order to evaluate the performance of the optimization, Standard deviation (SD) between releases, Reliability (Re), Resilience (Rs), Vulnerability (Vul) and SR are determined.

The reliability is expressed as:

$$R_e = n/N*100 \quad (9)$$

where: n: The total number of time period meeting the demand; N: The total number of considered time period.

Resilience is given by:

$$Rs=Ns/Nt \quad (10)$$

where: Ns: Number of satisfied time period followed by a failure and Nt : Number of total failure period.

SR denotes total optimal releases versus total demand of considered time period.

V. Results and Discussion

The active storage of the reservoir is discretized into 52 classes. The optimal cost for each month is determined based on (7) and the optimum releases are derived.

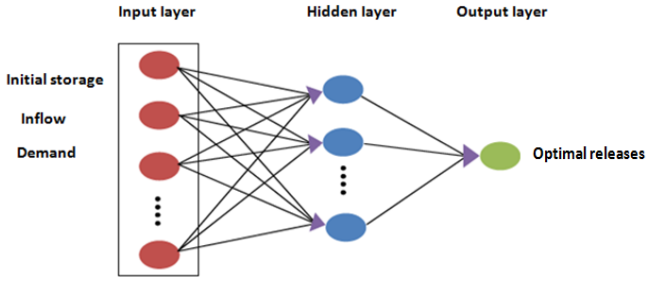


Fig. 4 Feed forward back propagation neural network

We have carried out a simulation of ANN by applying Levenberg-Marquardt algorithm. 75% from the data sets are taken for training step and 25% for validation. The inputs are: actual storage, inflow and demand, and the outputs are optimal releases derived from dynamic programming. The transfer function between hidden layers is sigmoid, and for the output layer we choose pure-line function.

TABLE III
Results of the Best Network

Epochs	2000
Neurons in first layer	9
Neurons in second layer	9
RMSE Training	0,4
RMSE Validation	0,43
Nash training	88,51
Nash validation	90,02
R^2	90

To obtain the best network, indicators performance as Nash–Sutcliffe (Nash), coefficient of determination (R^2) and root mean square error (RMSE) are listed in Table III.

Fig. 5 shows variation of the optimal releases obtained by PDNN.

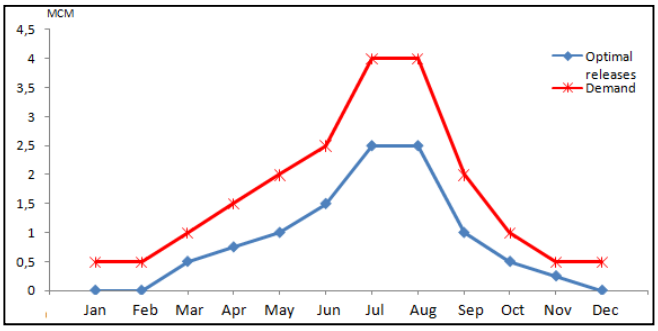


Fig. 5 Optimal operation rule obtained by PDNN

Fig. 5 shows variation of the monthly optimal releases computed by PDNN. We observed the ability to satisfy monthly demands for irrigation. The large gap between the optimal releases and demands was recorded in July and August.

TABLE IV
INDICES PERFORMANCE OPTIMIZATION OBTAINED BY PDNN

Indices	Historical releases	Optimal releases
Reliability (%)	2,5	52
Resilience	0,03	0,53
Ssatisfaction rate (%)	12,32	55

According to Table IV, we note an increase in the reliability from 2.5% to 52%. This indicates that the PDNN optimization better satisfies the irrigation demands. Also, the increase in the resilience from 0.03 to 0.53 means that the optimal releases obtained by PDNN meet the demands more frequently. Finally, SR is increased from 12.32% to 55%. This signifies that the optimal releases offer more quantities of water for irrigation.

VI. CONCLUSION

The main objective of the study is to minimize the gap between the water released from the dam's reservoir and the water demands for irrigation for Foum El-Gherza dam's reservoir system in south of Algeria. For this, DPNN method has been successfully applied for generating optimal operation rule. The comparative analysis about optimal releases obtained has been examined utilizing several statistical indicators including reliability, resilience and vulnerability. In addition, the operation rule generated using PDNN method could assure water volume to meet the irrigation demand. This allows to the dam management team to compensate the water shortage in the dry season by the one stored within the wet season, and hence avoiding the possible occurrence of risky water insufficiency during the operating of the reservoir. Finally, the proposed PDNN method showed its performance by providing more reliable and resilience operation for the examined case study.

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